

The “Cinderella Effect” and “Flutie Effect”: The Impact of Unexpected March Madness Runs
and NCAA Men’s Basketball Achievement on School’s Application Pools

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Abstract

This thesis investigates the Flutie and Cinderella effects in NCAA men's basketball programs, with a particular focus on their impact on college application pools. It explores how these effects vary across different time periods and between public and private institutions. Utilizing data from the 1989-1990 to the 2018-2019 NCAA Men’s basketball regular seasons, the study reveals the presence of both the Flutie and Cinderella effects in college basketball. Furthermore, it demonstrates that the influence of these effects differs not only over time but also between public and private schools, suggesting nuanced dynamics in how athletic success shapes institutional appeal.

KEYWORDS: (Cinderella effect, Flutie effect, College basketball programs, acceptance rate, enrollment)

On my honor, I have neither given nor received unauthorized aid on this
thesis

Signature: Ricardo Zhuang

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Introduction

On November 23, 1984, the Boston College Eagles football team played the Miami Hurricanes, the defending national champion. With six seconds remaining and his team trailing by four points, Boston College quarterback Doug Flutie threw a 48-yard touchdown pass to Gerard Phelan, completing the Eagles' upset victory. Flutie's outstanding performance produced institution-wide benefits for Boston College, mainly through expanding the application pools of the following years. Over the next two years, student applications increased by 30%. The phenomenon of schools receiving increased exposure and student applications following successful athletic performance were subsequently coined the "Flutie effect." Compared to the "front porch effect," which focuses explicitly on the impact of successful athletics on the school's visibility, the Flutie effect refers to successful athletics increasing student interest in the institution. Both the Flutie effect and the Cinderella effect impact the school's application pool similarly, however, instead of focusing on the overall athletic success, the Cinderella effect focuses on the impact of upset victories on the size of school's application pool.

Literature review

Multiple studies have investigated the relationship between athletic success and student quality for both basketball and football. Some studies focus on the impact of the school's sports culture on students' application and enrollment decisions. In contrast, other studies focus on the impact of upset victories and winning championships on students' application decisions in the following years.

Early research by Bremmer and Kesselring (1993) stated that successful athletic participation does not provide measurable academic benefits to the university, while a university's policy regarding admissions standards primarily determines the average level of freshman SAT scores. Pond (2021) also found that controlling for football and basketball team identification, as well as demographic variables, subjective perceptions of football or basketball successes are positive but insignificant predictors of the importance of athletics on students' enrollment decisions. By including "jock school" as a dummy variable, Alter and Reback (2014) found that the sports culture of the school is independent of students' application and enrollment decisions. Similarly, Tucker and Amato (2006) and Caudill et al. (2017) concluded that there is no consistent evidence that a highly successful basketball team has a favorable advertising effect on average SAT scores, while being in a major conference has a positive impact on schools' application pools. For football, Tucker (2005) found that athletic success has a robust, statistically significant positive impact on the quality of incoming first-year students after the formation of the Bowl Alliance in 1995, beginning with the incoming first-year class of 1996,

Cormier et al. (2023) and Eggers et al. (2021) found that winning a football championship positively affects peer rankings, alums giving, and student academic quality. Frank (2004) found similar results, but the effects are almost minimal. Collier et al. (2020) found that freshmen enrollments increased for private schools two years after making a surprise run in the men's NCAA basketball tournament. Toma et al. (1998) found that notable increases generally occurred in admissions applications received, both in absolute but, more importantly, relative to peer schools, in the years following the champion season. Additionally, the average college ranking from *U.S. News & World Report* for two years is significantly improved compared to the

two years before even though on-field improvement other than winning championship does not impact school ranking (Cox & Roden, 2010). Murphy and Trandel (1994) found that an increase in winning percentage by 25% of a university's football team tends to produce a 1.3% increase in applicants in the following year.

Several studies shed light on the differences in the impacts of either college basketball or football on the application pool of the school. Tucker and Amato (1993) compared both and found that a highly ranked football team on campus boosts average SAT scores over time, while there is no evidence that a highly ranked basketball team on campus impacts the average SAT scores.

While empirical studies have produced mixed results on the relationship between a school's sports success and the quantity and quality of students that apply to the school, Pope and Pope (2009) provided additional information on the indirect benefits that sports success provides to NCAA Division I schools. Their study showed that football and basketball success significantly increases the number of applications to a school, with estimates ranging from 2% to 8% for the top 20 football schools and top 16 basketball schools each year. They also found that private schools see increases in application rates after sports success that are two to four times higher than public schools.

Overall, and based on the related literature, we might expect a positive correlation between big-time basketball success and the application pool of the school by looking at two things: the acceptance rate and the number of enrolled students the year after school experienced an athletic success or upset victory in NCAA men's basketball tournament.

Table 1: Summary Statistics

Schools	Total Number		
Public Schools	240		
Private Schools	122		
Total	361		
Acceptance Rate (%)			
Samples	Mean	Median	Std. dev.
Full Sample	62.039	66.86	22.88
Public Schools	70.35	67.71	18.52
Private Schools	48.74	57.47	26.38
2000-2010	64.067	69.03	21.96
2010-2019	60.26	65.28	23.50
Enrollment			
Samples	Mean	Median	Std. dev.
Full Sample	22954.81	22101	14337.44
Public Schools	26506.38	25127	12842.47
Private Schools	14184.39	7171.5	14080.91
1990-2000	18247.85	17767	11240.91
2000-2010	20095.85	19962	11902.29
2010-2019	22954.81	22101	14337.44

NOTE: The data represent all colleges and universities participating in NCAA Division I Men's Basketball during the time period 1990-2019. Means and standard deviations of dependent variables are reported for each respective regression sample, with slight variation in sample sizes due to missing observations. All means and standard deviations of independent variables are reported for the applicant regression sample, which contains 6,263 observations. All real variables are reported in 2019-dollars. Acceptance rate is only reported starting in 2000 in our dataset, thus reducing the number of observations for these regressions. We report summary statistics for the full data sample and separately for the subset of private schools and public schools and the subset of different time periods. The data include 362 unique institutions representing 32 different conferences.

Data & Methodology

The data represent all colleges and universities participating in NCAA Division I Men's Basketball during the time period 1990-2019. It includes 6263 observations. All real variables are reported in 2019-dollars. Acceptance rate is only reported starting in 2000 in our dataset. The

data includes 362 institutions representing 32 different conference. We evaluate the application pool of the school through two perspectives: *Acceptance rate*, and *Enrollment*. Table 1 displays the mean, median, and standard deviation for all of the data used in our regression model. As one can see, public schools have lower acceptance rate and higher enrollment. As time goes on, both private schools and public schools have lower acceptance rate and higher enrollment.

Considered that different schools have unique, time-invariant characteristics that could influence both their athletic success and the size of their application pool, such as location, reputation, and so on, we employed a fixed effect model controlling for school and year fixed effects. The size of the application pool is expressed as a linear function of academic quality, athletic success, and annual and school fixed effects. The model generally takes the following functional form:

$$\text{Size of Application Pool} = f(\text{Academic quality, Athletic Success, Annual and school specific fixed effects})$$

Application pool related variables included in the model are defined as follows:

Acceptance rate is the percentage of applications accepted with respect to the number of total applications received. It is expressed as a percentage, encapsulating the selectivity of the institution. A decline in the acceptance rate typically signifies an increase in the number of applications received by the school for certain years, suggesting an expansion in the application pool compared to previous periods. A logarithmic transformation of the acceptance rate is used to reduce skewness.

Enrollment indicates the total number of students enrolled. This dependent

variable examines whether Flutie effect and Cinderella effect are considered in a student's final college decision. A logarithmic transformation of the enrollment is employed to reduce skewness.

Given that most schools have different tuition fees for students from the state and for out-of-state students. We decided to employ different models for out-of-state tuition fee and in-state tuition to capture the impact of the Flutie effect and Cinderella effect on students from the states and out-of-state students. Models take the following forms:

$$\text{Model 1 : Acceptance rate} = f(IFE, APP, SAPP, F4, CHAM, CE_1, CE_2, CE_3, CE_4, CE_5, C_T)$$

$$\text{Model 2 : Acceptance rate} = f(OFE, APP, SAPP, F4, CHAM, CE_1, CE_2, CE_3, CE_4, CE_5, C_T)$$

$$\text{Model 3 : Enrollment} = f(IFE, APP, SAPP, F4, CHAM, CE_1, CE_2, CE_3, CE_4, CE_5, C_T)$$

$$\text{Model 4 : Enrollment} = f(OFE, APP, SAPP, F4, CHAM, CE_1, CE_2, CE_3, CE_4, CE_5, C_T)$$

The source of the academic quality variables in the model is from various editions of *U.S. News America's Best Colleges* and *Peterson's Undergraduate Database*. It includes graduation rate, and tuition fee of the school for a certain year. The source of the athletic success is *The College Poll Archive*. Yearly fixed effects are included, recognizing that schools might have annual differences in the freshmen application pool. Athletic success variables include the final result of March Madness, the AP poll final rank, and a set of dummy variables for the Cinderella effect. Independent variables included in models are defined as follows:

IFE represents the annual tuition fee charged by the school for students from the state, adjusted for the Consumer Price Index (CPI) to reflect 2019 dollar values.

OFE represents the annual tuition fee charged by the school for out-of-state students, adjusted for the Consumer Price Index (CPI) to reflect 2019 dollar values.

The Public school dummy variable (PRI) has a value of one for a publicly funded academic institution and zero for a privately funded academic institution. Private schools are expected to have higher SAT scores, freshmen GPAs, and lower enrollment acceptance rates.

CE₁, CE₂, CE₃, CE₄, and CE₅ is a set of dummy variables for the Cinderella effect. The dummy variables CE₁, to CE₅ take a value of 1 if the school won against the school with higher seed and zero if it did not for certain rounds. CE₁ refers to upset victory in First round. CE₂ refers to upset victory in Second round. CE₃ refers to upset victory in Sweet Sixteen. CE₄ refers to upset victory in Elite Eight. CE₅ refers to upset victory in Final Four. March Madness consists of 68 teams competing in seven rounds of a single-elimination bracket: First Four, First round, Second round, Sweet Sixteen, Elite Eight, Final Four, and the Championship game. The Selection Committee determines the at-large bids, ranks all the teams from 1 to 68. Play-in round is not included in the analysis of Cinderella effect. Given that upset victory in Championship game is rare, it is not included in the analysis, either.

The tournament appearance dummy variable (APP) is one if the school made it to March Madness and zero if it did not. Participating in the play-in round is not considered as having made it to March Madness.

The final four dummy variable (F4) is one if the school made it to the Final four during that season and zero if the school did not.

Championship dummy variable (CHAMP) has a value of one if the school won the NCAA Division I men's basketball championship of that season and zero if the school did not. APP, F4, and CHAMP are included to examine the "cost-efficiency" of each level of March Madness achievement on expanding the school's application pool for the following academic year.

Long standing athletic success (SAAP) represents the times school made it to the tournament in the past 5 seasons. The variable is aiming to capture the impact of longstanding athletic success on the size of school's application pool.

Past literature shows mixed evidences on the impact of men's basketball program's achievement on the school's application pools while using different data from different time period. To test whether the impact of the Flutie effect and Cinderella effect keeps the same for different time periods or not, we decide to build a fixed effect model based on the hypothesis:

- *Hypothesis I:* the impact of athletic success on schools' application pools differs between different time periods.

Further more, given that public schools and private schools have different average enrollment and acceptance rate, they might be impacted by the Flutie effect and Cinderella effect

differently. Bremmer and Kesselring's (1993) study showed that athletic success impacts public and private schools differently. As a result, we decide to build a fixed effect model based on the hypothesis:

- *Hypothesis II*: the impact of athletic success on schools' application pools differs between public schools and private schools.

Conclusion

We acknowledge the potential for heteroskedasticity and serial correlation in our models, which could affect the reliability of the estimates. To address these concerns, we conducted the Arellano-Bond Test for serial correlation and the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity, as detailed in Appendices 1 and 2. The results indicate the presence of heteroskedasticity across all models, as evidenced by the significant outcomes of the Breusch-Pagan/Cook-Weisberg tests. However, the Arellano-Bond Test results reveal an absence of serial correlation in each model at the 5% significance level. These findings guide our choice of estimation techniques and the application of robust standard errors to account for the detected heteroskedasticity while ensuring the validity of our inferences in the absence of serial correlation. The OLS fixed effect regressions results for Model 1 and Model 2 are showed in Table 2. The OLS fixed effect regressions results for Model 3 and Model 4 are showed in Table 3. Table 4 and Table 5 show the OLS fixed effect regressions results for Hypothesis II. It appears that the Flutie effect and Cinderella effect impact the size of schools' application pools

differently. While we use acceptance rate as the indicator of the size of schools' application pools (Table 2), winning NCAA championship has negative relationship with the acceptance rate for all fixed effect model results, indicating a strong Flutie effect. Compared to the time period between 2000

Table 2: Estimated Regression Coefficients: Size of Application Pool Defined Using Log of Acceptance Rate

Variables	Full Sample	2000-2010	2010-2019	Full Sample	2000-2010	2010-2019
OFE	-0.0000103 (-5.93)***	-8.2*10 ⁻⁶ (-4.96)***	-0.000013 (-6.64)***	—	—	—
IFE	—	—	—	-7.06*10 ⁻⁶ (-1.74)*	-7.58*10 ⁻⁷ (-1.05)	-0.00002 (-6.09)***
APP	0.014 (0.86)	0.0036 (0.28)	0.0063 (0.53)	0.014 (1.36)	0.011 (0.83)	0.0085 (0.72)
SAPP	-0.0044 (-0.41)	-0.0078 (-1.01)	-0.013 (-1.37)*	-0.0026 (-0.21)	-0.0055 (-0.54)	-0.015 (-1.52)*
F4	-0.069 (-1.87)***	-0.048 (-1.72)	-0.055 (-1.61)**	-0.052 (-1.23)	-0.097 (-1.55)*	-0.0502 (-1.57)*
CHAM	-0.16 (-5.37)***	-0.32 (-10.25)***	-0.38 (-12.52)***	-0.15 (-4.31)***	Omitted	-0.38 (-12.83)***
CE ₁	-0.032 (-1.41)	-0.012 (-0.57)	-0.035 (-1.64)*	-0.034 (-1.5)*	-0.023 (-1.13)	-0.029 (-1.64)*
CE ₂	-0.047 (-1.41)	-0.08 (-1.21)	-0.095 (-1.48)*	-0.049 (-1.3)	-0.0025 (-0.08)	-0.094 (-1.38)
CE ₃	0.48 (1.15)	0.091 (1.4)	0.079 (1.14)	-0.068 (-1.58)*	-0.038 (-1.24)	0.079 (1.18)
CE ₄	-0.061 (-1.69)**	-0.062 (-1.34)	-0.077 (-1.83)**	0.0309 (0.81)	0.102 (1.43)	0.06002 (1.5)
CE ₅	-0.089 (-1.79)**	-0.045 (-0.38)	-0.11 (-1.85)**	0.0028 (0.05)	Omitted	-0.0824 (-1.59)*
R ²	0.23	0.15	0.14	0.18	0.24	0.11

NOTE: The dependent variable is the log of the acceptance rate; OFE=out-of-state tuition fee; IFE=in-state tuition fee; APP=tournament appearance dummy variable with one year lag; SAPP=times of tournament appearance in the past 5 years; F4=Final Four dummy variable; CHAM=NCAA men's basketball championship dummy variable; CE₁=first round Cinderella effect dummy variable; CE₂=second round Cinderella effect dummy variable; CE₃=Sweet 16 Cinderella effect dummy variable; CE₄=Elite 8 Cinderella effect dummy variable; CE₅=Final Four Cinderella effect dummy variable.

***p<0.05 level; **p<0.10 level; *p<0.15 level.

and 2010, the coefficient of Final Four dummy variable becomes more statistically significant

for time period between 2010 and 2019. Negative coefficient indicates that acceptance rate of the following academic year decreases when the team made it to Final Four. For Cinderella effect, it appears that only upset victories in Elite 8 and Final 4 are statistically significant for the full sample and between 2010 and 2019, indicating that upset victory in more important rounds lead to stronger Cinderella effect. Meanwhile, it is worth noticing that acceptance rate is more closely related to the out-of-state tuition fee compared to its in-state tuition fee. It does make sense, considering that advertising effect caused by upset victories impact out-of-state students more compared to it is for in-state students. Flutie effect and Cinderella effect are generally more significant for time period between 2010 and 2019 compared to the time period between 2000 and 2010. With the development of all kinds of social media, advertising effect caused by athletic success could be bigger and bigger.

However, if we divide them in public schools and private schools subsamples, the results of fixed effect model tells a different story. As it is showed in Table 3, it appears that private schools experience stronger Cinderella effect and Flutie effect compared to they are for public schools. Even with much less number of observations, tournament appearance, Cinderella effect of First Round, Cinderella effect of regional semifinal, and whether team made it to the Final 4 are more statistically significant for private schools compared to they are for public schools. Although private schools typically have a relatively smaller student population, they possess greater flexibility in the number of incoming freshmen. Consequently, they can be more easily impacted by other factors, such as the Cinderella effect and the Flutie effect.

Table 3: Estimated Regression Coefficients: Size of Application Pools Defined Using Log of Acceptance Rate

Variables	Public Schools	Private Schools	Public Schools	Private Schools
OFE	—	—		
IFE	-3.59*10 ⁻⁶ (-1.27)	-0.000016 (-3.87)***	—	—
APP	0.0076 (0.76)	-0.0452402 (1.72)**	0.0069 (1.23)	-0.00062 (-0.07)
SAPP	-0.0055 (-0.5)	0.0025 (0.09)	0.000707 (0.16)	-0.027 (-1.92) **
F4	-0.043 (-0.93)	-0.073 (-1.68)	-0.022 (-1.32)	-0.17 (-4.78)***
CHAM	-0.14 (-3.87)***	Omitted	-0.019 (-0.33)	Omitted
CE ₁	-0.0019 (-0.09)	-0.14 (-2.66)***	0.017 (1.31)	-0.017 (-0.61)
CE ₂	-0.063 (-1.59)*	0.04 (0.55)	0.0016 (0.13)	0.037 (1.32)
CE ₃	-0.051 (-1.33)*	-0.17 (-2.33)***	0.0071 (0.31)	-0.23 (-6.45)***
CE ₄	0.0308 (0.73)	Omitted	0.0045 (0.26)	Omitted
CE ₅	0.008 (0.16)	Omitted	0.019 (0.83)	Omitted
R ²	0.1	0.41	0.33	0.28

NOTE: The dependent variable is the log of the acceptance rate; OFE=out-of-state tuition fee; IFE=in-state tuition fee; APP=tournament appearance dummy variable with one year lag; SAPP=times of tournament appearance in the past 5 years; F4=Final Four dummy variable; CHAM=NCAA men's basketball championship dummy variable; CE₁=first round Cinderella effect dummy variable; CE₂=second round Cinderella effect dummy variable; CE₃=Sweet 16 Cinderella effect dummy variable; CE₄=Elite 8 Cinderella effect dummy variable; CE₅=Final Four Cinderella effect dummy variable.

***p<0.05 level; **p<0.10 level; *p<0.15 level.

While we use enrollment as the indicator of sizes of schools' application pools, both Flutie effect and Cinderella effect are less statistically significant. However, as shown in Table 4,

winning the championship has a positive relationship with the school's enrollment for the following academic year.

Table 4: Estimated Regression Coefficients: Size of Application Pool Defined Using Log of Enrollment

Variables	Full Sample	1990-2000	2000-2010	2010-2019	Full Sample	1990-2000	2000-2010	2010-2019
OFE	5.51*10 ⁻⁶ (3.65)***	1.68*10 ⁻⁸ (0.24)	7.45*10 ⁻⁶ (6.55)***	3.63*10 ⁻⁶ (4.47)***	—	—	—	—
IFE	—	—	—	—	3.31*10 ⁻⁶ (5.47)***	5.22*10 ⁻⁸ (0.24)	0.000012 (5.61)***	5.69*10 ⁻⁷ (0.89)
APP	0.0049 (1)	0.015 (2.96) ***	-0.008 (-0.97)	-0.0088 (-1.1)	0.0067 (1.28)	0.015 (2.97)***	-0.0096 (-1.24)	0.0069 (0.82)
SAPP	0.00701 (1.4)	-0.0027 (-0.61)	0.019 (2.65)***	0.0061 (1.12)	0.0076 (1.32)	-0.0027 (-0.61)	0.02 (2.87)	0.0069 (1.21)
F4	-0.014 (-0.89)	-0.00309 (-0.13)	0.0074 (0.63)	-0.12 (-0.9)	-0.0059 (-0.33)	-0.00303 (-0.13)	0.0105 (1.28)	-0.0029 (-0.16)
CHAM	0.049 (0.77)	0.0505 (1.69)**	0.037 (2.76)***	Omitted	-0.109 (-1.19)	0.052 (1.7)**	0.33 (2.49)***	Omitted
CE ₁	0.0095 (0.82)	0.012 (1.44)*	0.013 (0.58)	-0.0058 (-0.53)	0.0062 (0.51)	0.012 (1.45)*	0.0064 (0.31)	-0.013 (-1.26)
CE ₂	-0.0017 (-0.13)	0.015 (1.66)**	0.00409 (0.22)	0.0038 (0.33)	-0.004 (-0.25)	0.014 (1.65)*	0.0102 (0.55)	0.00909 (0.81)
CE ₃	0.014 (0.58)	0.02 (0.76)	0.031 (1.66)*	0.0035 (0.12)	-0.0204 (-0.88)	0.019 (0.75)	0.028 (1.63)*	0.0065 (0.22)
CE ₄	0.0088 (0.57)	-0.0107 (-0.44)	0.0098 (0.55)	0.0026 (0.15)	0.017 (0.89)	-0.0099 (-0.42)	0.016 (1.05)	-0.0059 (-0.27)
CE ₅	-0.0089 (-0.33)	-0.0061 (-0.29)	-0.0023 (-0.01)	0.018 (0.86)	-0.045 (-1.67)	-0.0059 (-0.28)	0.028 (1.45)*	-0.036 (-2.37)
R ²	0.26	0.1	0.15	0.15	0.16	0.11	0.24	0.11

NOTE: The dependent variable is the log of the enrollment; OFE=out-of-state tuition fee; IFE=in-state tuition fee; APP=tournament appearance dummy variable with one year lag; SAPP=times of tournament appearance in the past 5 years; F4=Final Four dummy variable; CHAM=NCAA men's basketball championship dummy variable; CE₁=first round Cinderella effect dummy variable; CE₂=second round Cinderella effect dummy variable; CE₃=Sweet 16 Cinderella effect dummy variable; CE₄=Elite 8 Cinderella effect dummy variable; CE₅=Final Four Cinderella effect dummy variable.

***p<0.05 level; **p<0.10 level; *p<0.15 level.

Similar to the trends observed when using acceptance rate as an indicator of the size of schools' application pools, the Flutie effect and Cinderella effect have a more pronounced impact

on the enrollment of private schools compared to public schools. In Table 5, Both upset in Second Round and made it to Final 4 has positive and statistically significant impact on the enrollment of private schools for the next year. A upset victory in second round is associated with

Table 5: Estimated Regression Coefficients: Size of Application Pools Defined Using Log of Enrollment

Variables	Public Schools	Private Schools	Public Schools	Private Schools
OFE	—	—		
IFE	4.62*10 ⁻⁶ (3.29)***	2.44*10 ⁻⁶ (3.56)***	—	—
APP	0.0084 (1.31)*	0.0025 (0.3)	0.0069 (1.23)	-0.0062 (-0.07)
SAPP	0.000801 (0.16)	0.028 (1.86)***	0.000707 (0.16)	0.027 (1.92)***
F4	0.011 (0.64)*	0.19 (5.74)***	0.022 (1.32)*	0.71 (4.78)***
CHAM	0.093 (1.22)	Omitted	-0.19 (-0.33)	Omitted
CE ₁	0.0097 (0.76)	-0.015 (-0.56)	0.017 (1.31)	-0.016 (-0.61)
CE ₂	-0.0064 (-0.37)	0.046 (1.67)*	0.0016 (0.13)	0.037 (1.32)*
CE ₃	-0.00096 (-0.05)	0.23 (6.4)*	0.0071 (0.31)	0.23 (6.45)***
CE ₄	0.018 (1.1)	Omitted	0.0045 (0.26)	Omitted
CE ₅	0.03 (1.11)	Omitted	0.019 (0.83)	Omitted
R ²	0.17	0.15	0.33	0.15

NOTE: The dependent variable is the log of the enrollment; OFE=out-of-state tuition fee; IFE=in-state tuition fee; APP=tournament appearance dummy variable with one year lag; SAPP=times of tournament appearance in the past 5 years; F4=Final Four dummy variable; CHAM=NCAA men's basketball championship dummy variable; CE₁=first round Cinderella effect dummy variable; CE₂=second round Cinderella effect dummy variable; CE₃=Sweet 16 Cinderella effect dummy variable; CE₄=Elite 8 Cinderella effect dummy variable; CE₅=Final Four Cinderella effect dummy variable.

***p<0.05 level; *p<0.10 level; *p<0.15 level.

4.6% increasing in enrollment for the next academic year. Meanwhile, longstanding athletic success has positive relationship with the enrollment of private schools. One more time of

tournament appearance in March Madness in the last five years lead to an 2.8% enrollment increase for the next academic year.

Overall, this study has embarked on a comprehensive exploration of the Flutie and Cinderella effects within the context of college applications, uncovering the multifaceted relationship between NCAA men's basketball achievement and academic appeal across different colleges and over varied periods. Both effects demonstrate significant temporal variability. It reflects an evolving landscape shaped by shifting societal values, demographic changes in the college application pool, and the transforming role of sports in higher education. Private schools are more likely to be impacted by these effects than public schools. This distinction likely reflects these two educational settings' inherent operational and promotional disparities. Generally, all independent variables of athletic success tend to have a negative relationship with schools' acceptance rate and a positive relationship with schools' enrollment, except winning the NCAA championship, which comes along with most former research, indicating that there is a Flutie and Cinderella effect on the number of college applications. Moreover, the positive relationship could be more credible, given that only a small proportion of schools won championships with respect to the whole dataset.

The thesis findings have significant implications for policy-making and strategic planning in college sports programs, especially for private institutions, where strategic investments in athletic programs could substantially influence student recruitment efforts. Furthermore, the temporal and institutional variability observed in the effects invites future research endeavors to delve deeper into the causal mechanisms and to explore prospective students' perceptions of collegiate athletic success.

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Appendix 1

Dynamic panel-data estimation, one-step difference GMM

Group variable: school_code	Number of obs	=	1917
Time variable : year	Number of groups	=	126
Number of instruments = 120	Obs per group: min	=	2
Wald chi2(0) =		avg =	15.21
Prob > chi2 =		max =	16

ln_ACC	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
ln_ACC						
L1.	.3737067	.0812734	4.60	0.000	.2144137	.5329997
v26	-7.41e-06	2.16e-06	-3.43	0.001	-.0000116	-3.18e-06
APP	.024199	.0824854	0.29	0.769	-.1374694	.1858674
CE1	-.2671342	.1834238	-1.46	0.145	-.6266383	.0923698
CE2	.1836968	.2974429	0.62	0.537	-.3992805	.7666742
CE3	.3863495	.3648405	1.06	0.290	-.3287246	1.101424
CE4	-.7416452	.7540391	-0.98	0.325	-2.219535	.7362443
CE5	1.44541	1.484054	0.97	0.330	-1.463283	4.354103
F4	.3034026	.4564142	0.66	0.506	-.5911529	1.197958
CHAM	-1.688632	2.048384	-0.82	0.410	-5.70339	2.326126
SAPP	.0367918	.0328672	1.12	0.263	-.0276268	.1012104

Instruments for first differences equation

GMM-type (missing=0, separate instruments for each period unless collapsed)
L(2/33).L.ln_ACC

Arellano-Bond test for AR(1) in first differences: z = **-4.47** Pr > z = **0.000**
Arellano-Bond test for AR(2) in first differences: z = **-1.79** Pr > z = **0.073**

Sargan test of overid. restrictions: chi2(109) = **206.15** Prob > chi2 = **0.000**
(Not robust, but not weakened by many instruments.)

Hansen test of overid. restrictions: chi2(109) = **115.42** Prob > chi2 = **0.319**
(Robust, but weakened by many instruments.)

Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of **ln_ACC**

H0: Constant variance

chi2(1) = **3561.45**
Prob > chi2 = **0.0000**

Appendix 2

Dynamic panel-data estimation, one-step difference GMM

Group variable: school_code	Number of obs	=	1906
Time variable : year	Number of groups	=	125
Number of instruments = 120	Obs per group: min	=	2
Wald chi2(0) =		avg =	15.25
Prob > chi2 =		max =	16

L_ENROLL	Robust					
	Coefficient	std. err.	z	P> z	[95% conf. interval]	
ln_ACC						
L1.	-.0586906	.0588586	-1.00	0.319	-.1740513	.0566701
v26	.0000118	2.62e-06	4.49	0.000	6.63e-06	.0000169
APP	-.027583	.0342929	-0.80	0.421	-.0947959	.0396298
CE1	-.0431346	.1260476	-0.34	0.732	-.2901833	.2039141
CE2	-.0690278	.2061977	-0.33	0.738	-.4731679	.3351124
CE3	-.1429876	.2112916	-0.68	0.499	-.5571114	.2711363
CE4	.5366559	.3123638	1.72	0.086	-.0755659	1.148878
CE5	-.2599632	.5934026	-0.44	0.661	-1.423011	.9030845
F4	-.2048365	.2426115	-0.84	0.399	-.6803463	.2706732
CHAM	-.4300447	.9642364	-0.45	0.656	-2.319913	1.459824
SAPP	.0261779	.0325109	0.81	0.421	-.0375422	.089898

Instruments for first differences equation

GMM-type (missing=0, separate instruments for each period unless collapsed)
L(2/33).L.ln_ACC

Arellano-Bond test for AR(1) in first differences: z = **-1.22** Pr > z = **0.222**
Arellano-Bond test for AR(2) in first differences: z = **1.28** Pr > z = **0.200**

Sargan test of overid. restrictions: chi2(109) = **188.40** Prob > chi2 = **0.000**
(Not robust, but not weakened by many instruments.)

Hansen test of overid. restrictions: chi2(109) = **112.57** Prob > chi2 = **0.388**
(Robust, but weakened by many instruments.)

Breusch-Pagan/Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of **L_ENROLL**

H0: Constant variance

chi2(1) = **149.50**

Prob > chi2 = **0.0000**