Student Debt and the Cinderella Effect*

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Abstract

Unexpected intercollegiate athletic success generates a variety of changes at universities – including increased salience and status of sports-oriented activities among students, known colloquially as the "Cinderella effect". By linking data on athletic contest outcomes, betting lines, student debt default rates, and post-college earnings data, we find that Cinderella events disrupt human capital development among incumbent students and adversely affect their financial outcomes. Following such events, treated students exhibit higher default rates and lower earnings. This effect strengthens with treatment exposure (results are larger for freshmen than seniors) and is concentrated in low-ranked universities. These institutions show no changes in revenues or expenditures, suggesting that resource-driven explanations are unlikely to be the primary driver. In contrast, students at high-ranked universities have marginally lower default rates and higher earnings, as these schools receive more applications, increase selectivity, and have marginally higher revenues and expenditures. Overall, our results suggest that athletic success shifts students' preferences away from academic focus. More broadly, our results show that universities affect human capital development, as distinct from selection effects that reflect assortive matching between students and universities.

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1 Introduction

Athletics are integral to the college experience at U.S. universities, with many students indicating that a university's reputation in athletics drives college choice.[1] However, whether academics and athletics ought to coexist is a long-standing debate. As American journalist William C. Rhoden writes, "College football is no more of a minor league than, say, the universities' schools of journalism, engineering, or music are. We can argue at another time whether football should occupy the same space on campus as those disciplines, but for now, it does." Despite the first-order importance of athletics to universities, there exists little research on how athletics affects students' human capital development during college or financial outcomes after graduation. This question is particularly relevant amid growing concerns over the value of a college degree, rising student debt burdens, and polarization over the role of universities in society.

Existing literature highlights the benefits of athletic success to universities, including advertising effects, increased applications, higher alumni donations, and improved graduation rates (e.g., McCormick and Tinsley, 1987; Tucker III and Amato, 1993; Murphy and Trandel, 1994; Mixon Jr and Hsing, 1994; Toma and Cross, 1998; Tucker, 2005; Pope and Pope, 2009; Anderson, 2017). However, survey evidence indicates that students increase alcohol consumption, reduce studying, and devote more time to partying in response to athletic success (Lindo et al., 2012). Predating this evidence, and in spite of winning multiple national championships, the University of Chicago famously abandoned intercollegiate football in 1939 due to concerns that big-time college football was incompatible with the university's academic mission.

The concern that athletic success encourages students to become more sports-oriented and less academically focused is well grounded in economic theories. Akerlof and Kranton (2000) develop an economic model of identity, defined by social categories and behavioral norms. They explain that identity evolves through social interactions and changes in social context, which can shift preferences and long-term behavior. When athletic success elevates the status and salience of a

[1] Fifteen percent of students report that athletics are a top factor of campus and student life that affects their college choice. See Students' Top Factors in College Choice and Admissions: 2023.

sports-oriented social identity, students' preferences may evolve accordingly, increasing the utility derived from sports-related activities and reinforcing leisure behavior at the expense of academic effort. This effect is lasting because social categories and their behavioral prescriptions (such as being a "sports fan" or a "studious academic") tend to become internalized as enduring components of one's self-image.

Complementing this framework, Brock and Durlauf (2001) present a discrete choice model incorporating social interactions, in which individuals' utility depends not only on personal preferences but also on the behavior of peers. Their analysis shows that social spillovers and conformity effects can produce stable equilibria, generating persistent shifts in preferences and actions. Applied to the context of college athletic success, such events can serve as catalysts that push campuses toward a sports-oriented equilibrium, where peer influence and social conformity (e.g., "we should all be sports fans") amplify students' preferences for sports-related leisure and reduce academic focus. This effect is also enduring: once established (e.g., "we rally around sports"), group-level behavioral norms tend to be self-reinforcing and persist over time, even with student turnover, as new entrants continually adapt to prevailing cultural norms. In line with this theoretical framework, Appendix B provides suggestive evidence that collegiate athletic success contributes to a shift in preferences from academic activities to sport-related leisure.

Given the potential long-term effect of athletic success, we analyze how it shapes students' human capital development and financial outcomes in the context of college football. Football is the biggest college sport, generating more revenue than the next 35 college sports combined.[2] The National Collegiate Athletic Association (NCAA) Division I Football Bowl Subdivision (FBS), formerly known as Division I-A, represents the highest level of college football competition. Division I-A reported that total athletic operating expenses exceeded $14 billion in 2024.[3] Our identification strategy exploits unexpected college football bowl game victories, which we refer to as "Cinderella events". Under the assumption that such unexpected outcomes are effectively random,

[2]The second-largest revenue-generating college sport is basketball, with football programs generating approximately four times the revenue of basketball programs. See Which College Sports Make the Most Money?

[3]See College Athletics Database.

any observed changes following the Cinderella events can be interpreted as the causal effects of athletic success.[4] These Cinderella events are particularly relevant in the context of Akerlof and Kranton (2000) and Brock and Durlauf (2001) because sudden athletic triumphs may sharply increase the salience and status of sports-oriented identities or utility among students, shifting their long-term preferences toward sports-related leisure activities.

Following Card and Dahl (2011), we define Cinderella events using college football betting market outcomes. Prior to each game, sportsbooks set a pregame betting line – a point spread – designed to balance wagers between teams. This line reflects the market's consensus on each team's relative strength. Comparing actual outcomes to these expectations allows us to classify wins or losses as either expected or unexpected. We define a treated university as one that unexpectedly wins a bowl game despite being at least four-point underdogs, and a control university as one that unexpectedly loses despite being favored by at least four points. Between the 2002 and 2019 academic years, 623 college football bowl games were played, of which we identify 122 Cinderella events involving 97 universities.

For each Cinderella event, we categorize students into three groups: (1) alumni cohorts who have graduated up to three years prior to the event, (2) incumbent cohorts (freshmen through seniors) enrolled during the event, and (3) Cinderella cohorts who enter in the first academic year immediately following the event. The alumni cohorts are presumed unaffected by the Cinderella events due to the lack of treatment, and thus serve as the benchmark. Among incumbent students, freshmen are likely to experience the largest impact, as long-term shifts in preferences away from academics toward athletics can adversely influence much of their remaining education in college. In contrast, upperclassmen (being closer to graduation) constitute partially treated cohorts – similar to the students in Eaton et al. (2020) who have completed at least one year of 2-year programs when their universities are bought by private equity investors. They are therefore less exposed to the

[4] The Cinderella effect is also referred to as the "Flutie effect". Anecdotal evidence suggests that this effect can shift student sentiment and campus culture. See The Flutie Effect: How Athletic Success Boosts College Applications. See also The Influence of Football on University Admissions and Campus Culture.

adverse effects of sports-related preference shifts. The Cinderella cohort, enrolling immediately after the event, may likewise receive substantial exposure to its consequences.

We compare student outcomes across these cohorts (i.e., the first difference) and contrast these differences between unexpected winners (treated universities) and unexpected losers (control universities) participating in the same game (i.e., the second difference), yielding a difference-in-differences framework.

We start by examining the student loan cohort default rate (CDR), obtained from the Federal Student Aid (FSA) office. The CDR is defined as the percentage of a school's borrowers who enter repayment on Federal Family Education Loans or Direct Loans and default within three years after entering repayment. Borrowers typically enter repayment after a six-month grace period that begins upon graduation or withdrawal from school. Because the cohort default rate captures the risk of loan default within a short period after graduation, it provides a proxy for human capital accumulation during college – students who have acquired valuable skills and knowledge are more likely to enhance their employment prospects and avoid default. We verify this mechanism in subsequent analyses.

As expected, we find no significant differences in student default rates among alumni cohorts between treated and control universities, supporting the parallel trends assumption in the absence of treatment. In contrast, default rates for incumbent cohorts at treated universities increase significantly following Cinderella events relative to their counterparts at control universities. The effect is strongest for freshmen and diminishes with student seniority. Incoming Cinderella cohorts also exhibit higher default rates relative to their control counterparts. Importantly, such Cinderella effects are primarily driven by treated universities that achieve unexpected victories, while students at control universities that unexpectedly lose show no significant changes in outcomes. These findings support the notion that shifts in student preferences toward greater sports orientation and reduced academic focus impede students' human capital accumulation and worsen loan repayment outcomes.

Moreover, we find significant heterogeneity in the Cinderella effects across university types. The effects are concentrated among relatively low-ranked universities, whereas high-ranked universities exhibit no significant changes in student loan default rates. In fact, default rates at high-ranked universities decline following Cinderella events, although the decrease is not statistically significant. This heterogeneity is in line with Aguiar et al. (2021), who show that preferences toward leisure have the largest impact on groups with lower opportunity costs of leisure or returns to skill. In our context, the concentration of Cinderella effects at lower-ranked universities suggests that students at these institutions are more vulnerable to shifts toward sports-related leisure, whereas students at high-ranked universities maintain their academic focus, likely due to the higher opportunity cost of non-academic pursuits.

To further explore the mechanisms underlying the Cinderella effects, we examine student earnings after graduation. We collect individual-level data on college enrollment periods, majors, and salary from Revelio Labs. We construct a sample that includes more than two million students who begin their undergraduate studies between 1995 and 2020, covering a wide range of majors, including business, engineering, education, economics, and biology. For each student, we collect the annual salary for six years after graduation. We then analyze the effect of Cinderella events on average earnings over both the short term (years 0 to 3 after graduation) and the long term (years 4 to 6 after graduation). We find that incumbent students and incoming Cinderella students at low-ranked treated universities earn lower salaries after graduation (relative to their respective control groups). As before, upperclassmen, who are less exposed to the Cinderella effects, do not exhibit such adverse earnings outcomes. These findings suggest that unexpected athletic success may hinder human capital acquisition and corroborate the observed increase in student loan default rates.[5]

We test the robustness of our results by employing an alternative identification strategy for athletic success – universities' bowl game appearances. After the regular season, FBS college

[5] In contrast, we show some evidence that students at high-ranked schools earn higher salaries, suggesting that students at these schools benefit from athletic success.

teams generally need at least six wins to qualify for a bowl game.[6] We compare universities that narrowly qualify for bowl games (i.e., those with a six-win regular-season record) to those that miss qualification (i.e., those with a five–win record) and thereby can not qualify for bowl games. Under the assumption – which we later verify – that universities winning five or six regular-season games are otherwise similar, differences in outcomes are driven by bowl game appearances. Rather than focusing on the outcomes of singular postseason bowl games, this alternative identification captures a university's success in football over the entirety of a season. Consistent with our main findings, students at universities that marginally qualify for bowl games experience higher student loan default rates and lower earnings after graduation.

Our main results suggest that at low-ranked schools, unexpected athletic success triggers shifts in student preferences toward sports-related activities, diverting their effort from academic pursuits. We next examine a few alternative explanations. We first consider peer effects. Athletic success may attract incoming students who are more football-oriented and less academically focused, potentially exerting negative peer influences on incumbent students. This is particularly the case for freshmen, who are likely to spend considerable curricular and extracurricular time with these incoming peers, thereby increasing their exposure to academically disengaged influencers. To test this possibility, we compare two groups of students: (i) freshmen on a typical four-year graduation track and (ii) juniors on an extended six-year track. When a Cinderella event occurs (typically in December or January), both groups have approximately 3.5 years remaining until graduation. However, freshmen are more closely connected to the incoming Cinderella cohort, whereas juniors have less proximity. Thus, while shifts in preferences may affect both groups similarly during their comparable time remaining in college education, the exposure to peer effects should differ. In this comparison, our earlier findings disappear, suggesting that peer effects are unlikely to be the primary mechanism driving our results.

We also consider a "resource constraint" explanation. Athletic success may attract a surge of applications from prospective students. Admitting additional students could strain university

[6] See Section 3.3 for additional details about bowl game eligibility rules.

resources, thereby reducing educational quality and leading to adverse student outcomes. This effect is again likely strongest for early-stage students, who have longer time remaining in college and are therefore more exposed to such institutional pressures. In this scenario, our findings are driven not by shifts in student preferences toward athletics but by universities' responses to increased demand. To examine this possibility, we analyze the changes in universities' applications, admissions, and financial conditions following Cinderella events. We find that low-ranked treated universities show no significant changes in applications, admissions policies, revenue, or expenditures – evidence inconsistent with the resource constraint explanation.[7]

Our paper contributes to several strands of literature. First, we contribute to the broad literature on college education and development of human capital. Studies identify determinants of such human capital formation, including financial shocks and resources (e.g., Lovenheim, 2011; Lovenheim and Reynolds, 2013; Charles et al., 2018; Chakrabarti et al., 2023; Cornaggia et al., 2024), the effectiveness of teachers and education (e.g., Maturana and Nickerson, 2020; Dinerstein et al., 2022; Gofman and Jin, 2024), and non-cognitive characteristics (e.g., Duckworth et al., 2007; Heckman et al., 2006; Cornaggia et al., 2021).

Closely related papers examine interventions aimed at improving postsecondary performance, including monetary incentives for schools and teachers (e.g., Lavy, 2002; Lavy, 2009; Goodman and Turner, 2013; Brownback and Sadoff, 2020), reducing college costs (e.g., Dynarski, 2002; Dynarski, 2003; Cornwell et al., 2006; Deming and Dynarski, 2009), providing students with information (e.g., Oreopoulos and Dunn, 2013; Bettinger et al., 2012; Bergman et al., 2019), and reducing complexity and uncertainty in college pricing (e.g., Dynarski et al., 2021). We contribute to this literature by providing evidence that athletic success, independent of educational resources, significantly shapes human capital development.

Prior studies document advertising benefits associated with athletic success, including increases in alumni donations (e.g., Brooker and Klastorin, 1981; Sigelman and Bookheimer, 1983; Baade and

[7]There is suggestive evidence that high-ranked schools receive more applications, become more selective, generate slightly higher revenue, and increase scholarship spending. These changes could help explain why students at high-ranked schools exhibit lower default rates and earn higher salaries after graduation.

Sundberg, 1996; Rhoads and Gerking, 2000; Tucker, 2004; Anderson, 2017), growth in applications (e.g., McCormick and Tinsley, 1987; Tucker III and Amato, 1993; Murphy and Trandel, 1994; Mixon Jr and Hsing, 1994; Toma and Cross, 1998; Tucker, 2005; Pope and Pope, 2009; Anderson, 2017), and improvements in graduation rates (e.g., Tucker, 2004).

However, collegiate football is also associated with distraction from academic pursuits and lower performance (Glassman et al., 2007; Rees and Schnepel, 2009; Glassman et al., 2010), suggesting students invest less effort in academics. For example, Lindo et al. (2012) examine the impact of athletic success on academic performance at the University of Oregon and find that it lowers student grades, particularly among male students with low SAT scores. Similarly, Metcalfe et al. (2019) document that international football ("soccer" in American parlance) tournaments negatively affect student academic performance in England. We contribute to this literature by studying the causal effects of athletic success on students' financial outcomes. In particular, we focus on student loan repayment, an issue central to recent political debates and one that carries significant implications for individuals' creditworthiness and access to credit markets.

In this regard, we also contribute to the growing literature on the determinants of student debt outcomes (e.g., Looney and Yannelis, 2015; Looney and Yannelis, 2022; Armona et al., 2018; Mueller and Yannelis, 2019; Parise and Peijnenburg, 2019; Eaton et al., 2020; Yannelis and Tracey, 2022; Cornaggia and Xia, 2024). We extend this literature by isolating the effects of college athletic programs from the influence of students' pre-college characteristics and the cost of education. Our study identifies a previously underexplored factor that may have a significant impact on student loan outcomes.

2 Data desription

2.1 Sports betting data and Cinderella events

In our main analyses, we identify Cinderella events as college football bowl games that beat betting market expectations. Betting markets are particularly valuable in this context because they represent a publicly observable and likely unbiased forecast of game outcomes that aggregates information from a wide variety of sources, including expert assessments, team statistics, injury reports, and historical performance trends. Prior research in finance and economics frequently relies on betting markets as proxies for ex ante expectations, given their ability to incorporate information in real time (e.g., Card and Dahl, 2011).

To construct our dataset, we collect betting lines and game outcomes from Sportsbook Review and Odds Shark, two widely used repositories of historical wagering data. The betting line represents the number of points by which the favored team is expected to win, which provides us with a clean measure of relative expectations. For instance, if Team A is favored by four points, a bet on Team A pays off only if the team wins by more than four points. If Team A wins by exactly four points, the result is considered a "push" and wagers are refunded. We exclude push games from the analysis to ensure that our definition of unexpected outcomes strictly reflects cases in which realized results diverge from expectations.

A Cinderella event is a game in which a university unexpectedly wins a bowl game despite being underdogs by at least four points in the betting (i.e., the treated university), while its opponent unexpectedly loses despite being favored by at least four points (i.e., the control university). The 4-point threshold is chosen to ensure that the outcome is unlikely to reflect random variation around a balanced line and instead captures a substantial surprise.[8]

Between the 2002 and 2019 academic years, we identify 122 Cinderella events. Table A1 lists these Cinderella events, along with the treated and control universities in each event. We also present the treated universities ranking based on the 2002 U.S. News rankings and the 2025 Forbes rankings. We categorize universities into three groups: low-rank, middle-rank, and high-rank, according to their respective rankings. In our analyses, we examine the heterogeneous effect of Cinderella events on students depending on university ranking.[9]

[8]Our main results are robust to a 3-point or 5-point threshold.
[9]If the 2002 U.S. News ranking data are unavailable, we refer to the 2025 ranking.

For each Cinderella event, we categorize students from the treated and control universities into three groups: (i) *alumni cohorts* who graduated before the event – including those who completed their studies three years, two years, or one year prior, as well as those graduating immediately before the event, (ii) *incumbent cohorts* who are enrolled at the university during the event as freshmen, sophomores, juniors, or seniors, and (iii) the *Cinderella cohort* – consisting of students entering college in the academic year immediately following the event. Our analysis first compares student outcomes across different cohorts (the first difference), and then contrasts these outcomes between treated and control universities (the second difference), yielding a difference-in-differences framework.

To contextualize the Cinderella events, it is worth noting that the bowl system carries important institutional significance. Bowl games often take place during the winter break period, which means that campus sentiment builds in anticipation of the event and lingers into the following semester. Media coverage surrounding such games is disproportionately high compared to regular-season contests, amplifying the cultural salience of a victory or loss. These characteristics make bowl games particularly suitable for studying how sudden changes in athletic success filter through to student outcomes.

2.2 Cohort default rate and earnings after graduation

For each treated (or control) university associated with a Cinderella event, we collect data on student loan cohort default rates and earnings after graduation. Cohort default rate (CDR) data are obtained from the Federal Student Aid (FSA) office, covering academic years 1999 (three years before the earliest Cinderella event) through 2016. For each school, the CDR is defined as the percentage of its borrowers in a given cohort who enter repayment on Federal Family Education Loans (FFEL) or William D. Ford Federal Direct Loans and default within three years of entering repayment.[10] For most federal student loans, borrowers enter repayment six months after graduation. The "cohort"

[10]The FFEL loans included subsidized and unsubsidized Federal Stafford Loans. The Direct Loans include Federal Direct Subsidized Stafford/Ford Loans and Federal Direct Unsubsidized Stafford/Direct Loans.

used for CDR calculation consists of borrowers who began repayment during a federal fiscal year (October 1 through September 30 of the next year). For example, the 2010 cohort includes borrowers entering repayment between October 1, 2010, and September 30, 2011. Typically, these borrowers would have graduated in September 2010, and they are classified as seniors in academic year 2009 (spanning fall 2009 to summer 2010), juniors in 2008, sophomores in 2007, and freshmen in 2006. Thus, if a Cinderella event occurred in academic year 2007, this cohort is in its sophomore year when the event took place.

We obtain earnings information from Revelio Labs. Revelio Labs compiles workforce data from publicly available online profiles and job postings. The data contain detailed education and professional histories of individuals, including the universities they attend (with the period of attendance), employment roles, salary, seniority, and geographic location. We first identify individuals who belong to the *alumni cohorts*, *incumbent cohorts*, or *Cinderella cohorts* of the universities associated with each Cinderella event. Then, for each individual, we collect up to six years of annual salary records beginning from the year of graduation.[11] We require that individuals have at least one year of salary information within the six-year window after graduation in the Revelio database.

[Insert Table 1 here.]

Table 1 Panel A presents summary statistics on student loan cohort default rates and earnings after graduation in our sample. The average default rate is 4.01%, with a standard deviation of 2.63 percentage points. Average earnings in the year of graduation (Year 0) are $50,170, with a standard deviation of $26,690. Earnings increase gradually following graduation. The average earnings over the first three years after graduation (Years 0–3) are $56,570, with a standard deviation of $27,480, while the average earnings between Years 4 and 6 rise to $67,580, with a standard deviation of $34,490.

[11] For the latest Cinderella events occurring in 2019, the Revelio data are available through 2024.

2.3 University characteristics

We collect data on university characteristics from the Integrated Postsecondary Education Data System (IPEDS). We gather information on the number of applicants to each university, admitted students, enrolled students, and the 25th and 75th percentile SAT scores of enrolled students. Table 1 Panel B reports summary statistics for these university characteristics. On average, universities in our sample receive 19,650 applications per year, admit 10,840 students, and enroll 4,070 students. The average acceptance rate is 62.26% with a standard deviation of 19.25%, and the average admission yield is 40.16% with a standard deviation of 12.00%. The average 25th percentile SAT score is 1,077.03, and the average 75th percentile SAT score is 1,293.63.

In addition, we collect data on universities' financial conditions from the IPEDS. On average, our sample universities generate $1.48 billion in total revenue per year, with a standard deviation of $1.46 billion. The average revenue from tuition and fees is $295.55 million. Average revenues from grants, contracts, and appropriations are $206.49 million from federal sources, $237.39 million from state sources, and $130.79 million from local and private sources, respectively. Universities generate an additional $125.73 million on average from auxiliary enterprises. The average total expense is $1.37 billion per year with a standard deviation of $1.33 billion. Universities spend $349.69 million on instruction, $233.83 million on research, and $101.76 million on academic support activities. Average expenses on public service, institutional support, scholarships, and auxiliary enterprises are $76.51 million, $84.85 million, $34.28 million, and $136.55 million, respectively.

3 The Cinderella effect on human capital development

3.1 Student debt outcomes

To illustrate our empirical approach, consider a Cinderella event in which university *W* unexpectedly wins a game (the treated university), while university *L* unexpectedly loses this game (the control).

We analyze outcomes for three student groups – comprising a total of nine cohorts – associated with university *W* as follows.

As defined in Section 2.1, the four *alumni cohorts* include students who graduated three, two, or one year prior to the event, as well as those graduating immediately before the event; these individuals are presumed to remain unaffected by the Cinderella event, given their lack of exposure to the treatment, and thus serve as the benchmark group. Among the *incumbent cohorts* – students enrolled at university *W* at the time of the event – we expect the largest impact of the Cinderella event to occur among freshmen, who will spend the greatest amount of time on campus post-event. The effect is anticipated to attenuate for sophomores, juniors, and seniors, who have progressively less remaining time at the university. Additionally, the *Cinderella cohort*, consisting of students matriculating in the academic year immediately following the event, may also receive substantial exposure to the Cinderella event.

Following this intuition, we compare student outcomes across the nine cohorts of the treated university *W* (the first difference), and then contrast these outcomes with those of the control university *L* (the second difference), yielding a difference-in-differences design. The control university helps mute any generic factors contemporaneous with each Cinderella event that might influence educational quality, students' human capital acquisition, and subsequent outcomes such as loan default.

Specifically, we begin with a graphical analysis estimating the following equation using ordinary least squares (OLS):

$$
\begin{aligned}
Cohort\ Default\ Rate\ \%_{i,c} = \sum_{c=1}^{9} \beta_c \boldsymbol{Cohort}_c \times Treated_i + \sum_{c=1}^{9} \delta_c Cohort_c + \gamma_i Treated_i \\
+ Fixed\ effects + \epsilon_{i,c}, \qquad (1)
\end{aligned}
$$

where i indexes universities and c indexes cohorts. The independent variable is the CDR for each cohort c of university i. $Treated_i$ is an indicator equal to one for universities that unexpectedly win a bowl game. $Cohort_c$ are individual indicators for the nine student cohorts ($Cohort_c \in \{$*3Yr*

Alumni, *2Yr Alumni*, *1Yr Alumni*, *Graduates*, *Senior*, *Junior*, *Sophomore*, *Freshman*, *Cinderella*$\}$). The default rate for students graduating immediately before the Cinderella event, i.e., *Graduates*, serves as the reference group (omitted from the estimation). Each coefficient β captures how the impact of the Cinderella event for a given cohort differs between the winning (treated) and losing (control) universities.

In this estimation, we include $University$ fixed effects to control for time-invariant differences across universities. We also include $Game\ Pair$ by $Year$ fixed effects, which restrict comparisons to universities that played against each other in the same bowl game in a given year (i.e., a Cinderella event). Standard errors are clustered at the university level to account for serial correlation and at the year level to account for cross-sectional correlation.

[Insert Figure 1 here.]

As suggested by Lindo et al. (2012) and Metcalfe et al. (2019), students who are less academically prepared before college are more susceptible to distraction arising from collegiate athletic success. Therefore, we estimate Equation (1) separately based on university type: low-ranked, middle-ranked, and high-ranked (see Table A1 for the classification).

Figure 1 displays the estimated coefficients β for each cohort. The bars surrounding each coefficient represent the 5% and 95% confidence intervals. The red line in Figure 1 plots the estimates for low-ranked schools. We find no significant differences in default rates for the 1-year, 2-year, and 3-year alumni cohorts between treated and control universities (benchmarked against the reference cohort). This observation supports the parallel trend assumption prior to the Cinderella events. In contrast, default rates for the incumbent and Cinderella cohorts in the treated universities significantly increase relative to those of the corresponding cohorts in the control universities. As expected, the magnitude of these effects increases progressively and is strongest for freshmen and Cinderella cohorts, who have the longest remaining time on campus following the event.

Among students enrolled in treated middle-ranked universities (represented by the green line), there is a moderate increase in the probability of student debt default relative to those at control universities, particularly pronounced for the freshman cohort. In contrast, students at high-ranked universities exhibit no significant differences in changes in default rates for the Cinderella or incumbent cohorts following the event, when comparing treated and control institutions.

One concern is that the patterns observed among low-ranked universities may be driven predominantly by the control group, which could experience adverse changes (e.g., reductions in educational resources) following an unexpected loss. However, this argument would imply that students from these control universities are more likely to default than those from the treated universities – an outcome contradicted by the trajectory of the red line in Figure 1. Nevertheless, to explicitly address this concern, Figure A1 in Online Appendix separately plots the average cohort default rates for low-ranked treated and control universities. The figure reveals a pronounced spike in default rates among incumbent and Cinderella cohorts at the treated universities, while default rates remain relatively stable across all cohorts at the control universities. This evidence suggests that the patterns observed in Figure 1 are unlikely to be driven by the losing universities.

We formalize the graphical analyses Figure 1 by estimating the following equation and report the results in Table 2:

$$Cohort\ Default\ Rate\ \%_{i,c} = \sum_{c=1}^{6} \beta_c \boldsymbol{Cohort}_c \times Treated_i + \sum_{c=1}^{6} \delta_c Cohort_c + \gamma_i Treated_i + Fixed\,effects + \epsilon_{i,c}, \tag{2}$$

Equation (2) follows the same intuition as Equation (1). To conserve space, we collapse the four *alumni cohorts* – which have all demonstrated no significant impact following the Cinderella event – into a single baseline group (omitted from the estimation). Then, $Cohort_c$ are individual indicators for the six student cohorts ($Cohort_c \in \{$*Graduates and Alumni*, *Senior*, *Junior*, *Sophomore*, *Freshman*, *Cinderella*$\}$). We perform the estimation separately for the low-ranked, middle-ranked, and high-ranked universities as in Figure 1.

Table 2 reports the results. Column (1) includes $University$ fixed effects to control for time-invariant differences across universities and $Year$ fixed effects. Column (2) includes $University$ fixed effects and $Game\ Pair$ by $Year$ fixed effects. The results show that the default rate for incumbent students increases from senior to freshman cohorts, consistent with the pattern in Figure 1. This effect is economically meaningful. Based on column (1), the default rate for freshman cohorts in treated universities is 1.238 percentage points higher than that for freshman cohorts in control universities, representing approximately 31 percent of the mean default rate in our sample (1.238/4.01). This magnitude is larger in column (2).

[Insert Table 2 here.]

The Cinderella cohort at treated universities, who enroll in the first academic year immediately following the event, is also more likely to default on their student loans compared to their counterparts at control universities. The cohort default rate increases by 1.059 or 1.390 percentage points (relative to the control) following Cinderella events. This evidence suggests that the distraction from athletic success extends to incoming students, either because they are drawn to the school by the athletic achievement or because the overall campus sentiment changes in ways that affect them after the Cinderella events.

3.2 Labor market outcomes

Next, we investigate the mechanism through which Cinderella events may influence student debt default risk. Prior research suggests that athletic success can create distractions, including increased alcohol consumption and decreased academic effort, which may hinder educational attainment (Lindo et al., 2012). Consequently, graduates with lower academic achievement may face diminished labor market competitiveness, resulting in lower earnings and a higher likelihood of loan default. Following this intuition, we examine whether students affected by Cinderella events earn less after graduation.

[Insert Figure 2 here.]

Specifically, we estimate Equation (1), replacing the dependent variable with the log-transformed students' average salary from Year 0 to Year 3 after graduation.[12] Figure 2 plots the coefficient estimates for each cohort, omitting those graduating immediately before the Cinderella events as the

[12] We only keep students with non-zero salary information

baseline. Student earnings between the treated and control universities do not differ significantly for the alumni cohorts, supporting the parallel trends assumption. In contrast, incumbent students at low-ranked treated universities (the red line) earn significantly less than their counterparts in the control group, particularly the sophomore and freshman cohorts. Earnings for Cinderella cohorts at treated schools are also significantly lower. These patterns corroborate our earlier findings regarding student default rates. Students at middle-ranked schools experience negative earnings effects, as shown by the green line, while students at high-ranked schools earn higher salaries after graduation, as shown by the blue line.

In Figure 3, we further examine whether the Cinderella effect on earnings persists in the longer term by analyzing differences in average salary from Year 4 to Year 6 after graduation. It indicates that the patterns in labor market outcomes persist for at least six years after graduation.

[Insert Figure 3 here.]

Table 3 presents a similar analysis as in Table 2. It estimates Equation (2), replacing the outcome variable with students' average salary from Year 0 to Year 3 after graduation. Columns (1) and (2) report estimates for low-ranked universities. In column (1), we find that incumbent students who experience unexpected athletic success earn lower salaries after graduation relative to those who experience the loss. Specifically, the sophomore and freshman cohorts earn 1.5 percent less annually on average, and the Cinderella cohort earns 2 percent less, echoing the higher default risk observed for these cohorts in Table 2. We note, however, that the earnings sample includes all individuals enrolled in treated and control universities, rather than only those with student loans, because the Revelio database does not provide student aid information. Thus, the earnings sample is broader than the cohorts included in Table 2 regarding student debt default. For this reason, the observed 2 percent reduction in annual earnings may not directly translate into the increased default rates documented earlier. We focus primarily on the qualitative association between reduced earnings and elevated default rates, rather than asserting a precise quantitative linkage.

Column (2) adds $Game\ Pair$ by $Year$ by $Major$ fixed effects, restricting comparisons to students who graduate in the same year, major in the same field, and attend treatment and control universities that played in the same bowl game. The results remain consistent under this stricter identification strategy.

[Insert Table 3 here.]

Incumbent students and Cinderella cohorts at middle-ranked schools also earn less after graduation. The freshman and Cinderella cohorts at treated universities earn 1.6 percent and 2.4 percent less, respectively, compared to students at control universities. In contrast, high-ranked universities exhibit positive Cinderella effects. As shown in column (5), the Cinderella cohorts earn 1.5 percent more, respectively, after graduation. However, these positive earnings effects do not translate into lower default rates, as shown in columns (5) and (6) of Table 2. This is likely because students from high-ranked universities tend to earn higher base salaries to begin with, rendering their default rates less sensitive to changes in earnings. Table 4 repeats the analyses using longer-term earnings and shows that similar Cinderella effects persist for at least six years after graduation.

Overall, the results in this section suggest that athletic success can divert students' attention away from academics, particularly for students at low-ranked universities. Incumbent and incoming students at low-ranked universities experiencing unexpected athletic success are more likely to default on their student loans, as they are less competitive in the labor market and earn lower salaries after graduation.

3.3 Alternative identification: The bowl game appearance

Our analyses so far identify the effect of athletic success using unexpected bowl game outcomes. We next use an alternative identification strategy based on bowl game appearance. Specifically, we exploit variation in a college team's eligibility and likelihood of appearing in a post-season bowl game, depending on (i) the number of regular-season games, and (ii) the prevailing eligibility rules during our sample period from 2002 to 2019.

First, before 2006, most college teams played 11 regular-season games, and thus, achieving six wins substantially increased the likelihood of earning a bowl appearance. Two exceptions occurred in 2002 and 2003, when there were 14 Saturdays between the permissible start date and the final regular-season weekend in November. During these years, teams played 12 games, and as a result, winning six games did not sharply distinguish teams from those with only five wins in terms of bowl eligibility.

Second, beginning in 2006, all teams played 12 regular-season games. Starting in 2010, however, the NCAA gradually relaxed the criteria for bowl eligibility, eventually permitting teams with losing records (five wins and seven losses) to participate. Consequently, after 2010, winning six games once again substantially increases the likelihood of a bowl appearance.

Figure 4 illustrates these patterns. The figure plots the probability that a college team appears in a post-season bowl as a function of its total wins. Panel A covers seasons with 11 regular-season games and periods when the NCAA maintained a lower eligibility threshold in our sample (i.e., 2004, 2005, and 2010 onward). The figure shows that the probability of appearing in a bowl game rises sharply – from nearly zero for teams with five wins to approximately 80 percent for those with six wins. The probability approaches 100 percent when a team wins seven or more games. We refer to these seasons as the "high-six" seasons. Panel B, in contrast, includes seasons with 12 games and stricter eligibility standards (2002, 2003, and 2006–2009). In these years, the increase in bowl game probability from five to six wins is more moderate compared to Panel A. We refer to these seasons as the "low-six" seasons.

[Insert Figure 4 here.]

Based on these patterns, we construct the following identification strategy. For each regular season, we select teams that have won five games. Among them, we then identify those that secure a sixth win as the treated group. Teams that fail to win any additional regular-season games serve as the control universities.[13] We derive two predictions. (i) In the "high-six" seasons, we expect student default rates and earnings for the treated group (universities with six wins) to differ significantly from those of the control group (universities with five wins). Assuming that universities with similar regular-season records are otherwise comparable, these differences can be attributed to bowl game

[13] As shown in Figure 4, almost none of these schools will appear in bowl games.

appearances. (ii) In the "low-six" seasons, we expect no significant difference between the treated and control groups, which would validate the assumption that five- and six-win universities are similar in the absence of bowl appearances. Conversely, if these institutions are fundamentally different, such differences would continue to manifest during the "low-six" seasons. This alternative identification captures a university's success in football over the entirety of a season, instead of singular postseason bowl games.

To maintain consistency in terminology, we refer to winning the 6th game as a "Cinderella event," acknowledging that this occurrence carries less of a surprise element than the primary analyses based on betting lines. For each event, we follow Section 2.1 to identify three student groups: the *alumni cohorts*, *incumbent cohorts*, or *Cinderella cohorts*. We then compare student outcomes at treated universities with those at control universities across these cohorts, employing the difference-in-differences framework similar to our main analyses (Equation (1) and Equation (2)).

We start with the sample of the "high six" seasons. Figure 5 plots the estimated differences in cohort default rates between treated and control universities across cohorts, using the graduate cohort as the baseline. The estimation follows a similar manner to Figure 1. The results indicate that default rates followed parallel trends prior to bowl game appearances. For low-ranked treated universities, default rates for the incumbent and Cinderella cohorts – who have the longest remaining time in school – are significantly higher than those in the control group. We do not see such a pattern for middle- and high-ranked universities, consistent with Figure 1.

[Insert Figure 5 here.]

Table 5 further confirms these results. In column (1), which includes $University$ and $Year$ fixed effects, the freshman cohort at low-ranked treated schools has a 1.185 percent higher default rate than the corresponding cohort at control schools, while the Cinderella cohort has a 1.807 percent higher default rate. Column (2) includes $University$ fixed effects and $Game\ Year \times Year$ fixed effects, restricting comparisons to treated and control schools with five or six wins in the same event year. The results remain similar. Columns (3) through (6) show little evidence of significant changes in default rate for middle-ranked schools or high-ranked schools. Overall, these findings are consistent with our main results, indicating that athletic success can shift preferences toward sports-related leisure and create a distraction for incumbent and incoming students.

[Insert Table 5 here.]

In Online Appendix Figure A2 and Table A2, we further examine the effects of bowl game appearances on labor market outcomes. Lower earnings for the incumbent and Cinderella cohorts at treated low-ranked schools likely explain their higher default risk.

We replicate the analyses using the "low-six" sample and find no notable effects on either student debt default or post-graduation earnings, as predicted. Specifically, Panels A and B of Figure 6 show no statistically significant differences in these outcomes between treated and control universities across any cohort for low-ranked schools. This absence of effects supports the assumption that five- and six-win universities are comparable in the absence of bowl appearances and thus, suggests that the results observed in the "high-six" sample are primarily driven by bowl game participation.

[Insert Figure 6 here.]

4 Alternative explanations

4.1 Peer effects

Our findings so far support the notion that athletic success creates a distraction for incumbent (or newly enrolled) students, hinders human capital acquisition, and negatively affects career outcomes and loan repayment. In this section, we consider a few alternative explanations to our main hypothesis.

We start by considering the possibility of peer effects. Specifically, athletic success may attract students who are more football-oriented and less academically focused. These students may, in turn, exert negative peer effects on incumbent students – particularly the freshman cohort, who likely spend substantial curricular or extracurricular time with them. This mechanism is plausible given our observation that the Cinderella cohort exhibits worse outcomes following the event, making them potential transmitters of such negative effects.

To examine this possibility, we compare the freshman cohort, which is closely connected to the Cinderella cohort, with the junior cohort, which is less proximate to the Cinderella cohort but has the *same* amount of time remaining in college. Specifically, the sample now includes two groups of students: (i) the freshman cohort that takes four years to graduate, and (ii) the junior cohort that takes six years to graduate – namely, the six-year juniors. When the Cinderella event (as defined in Section 2.1) occurs in December or January, both the freshmen and six-year juniors have around 3.5 years remaining until graduation. Therefore, while the potential for distraction due to athletic success is similar across the two groups, the extent of peer effects differs because of their varying proximity to the incoming football-oriented students. If peer effects play a role in explaining our findings so far, then we would expect those results to persist in this setting.

Following this intuition, we estimate the following specification:

$$\begin{aligned} Log(Avg.\ Salary\ (Year\ 0\ to\ Year\ 3)^{u}_{i,c}) = {} & \beta_c Freshman_c \times Treated_i + \delta_c Freshman_c \\ & + \gamma_i Treated_i + Fixed\ effects + \epsilon^{u}_{i,c}. \end{aligned} \tag{3}$$

Because this test requires precise information on students' time to graduation (i.e., four years versus six years) – information not available from the FSA data – we rely on students' college enrollment dates reported in the Revelio dataset to conduct the test. Consequently, the outcome variable for this analysis pertains only to student earnings after graduation. Based on prior observations, we restrict our analysis to low-ranked universities, given the absence of significant results for middle- and high-ranked counterparts.

Equation (3) follows the same structure as Equation (2). The key difference is that here the sample includes only two cohorts of students, where $Freshman_c$ is an indicator equal to one for the freshman cohort and zero for the six-year juniors. Other variables are defined as in the main analysis. The coefficient β captures the effect of Cinderella events on earnings for the freshman cohort relative to the junior cohort in treated universities (who have the same number of years remaining in college but are less proximate to the Cinderella cohort), benchmarked against the control universities. If our previous results are driven by peer effects, then we would expect β to be negative, indicating that the freshman cohort earns lower salaries than the junior cohort because they are closer to the Cinderella cohort.

[Insert Table 6 here.]

Table 6 presents the results. We find that relative to control universities, earnings for the freshman cohort at the treated universities are not significantly lower than those for the junior cohort. It suggests that peer effects from the Cinderella cohort are unlikely to explain our previous findings.

4.2 Universities' applications and financial conditions

It is also possible that athletic success attracts a surge of applications from prospective students. Admitting these additional students may strain university resources, thereby diminishing educational quality and leading to adverse student outcomes. This "resource constraint" hypothesis is particularly relevant for early-stage students, who have more time remaining in college and are therefore more exposed to such institutional pressures. In this case, it is not the euphoria stemming from athletic success that drives our findings, but rather the university's indirect response to increased demand.

To examine this possibility, we investigate universities' responses to Cinderella events, as reflected in the number of applications received, the acceptance and admission rates, and university financial conditions. We estimate the following specification:

$$Y_{i,t} = \beta_s Treated_i \times Post_t + \delta_t Post_t + \gamma_i Treated_i + Fixed\,effects + \epsilon_{i,t}. \quad (4)$$

The Cinderella events are defined in the same way as in Section 2.1. However, the dependent variables of interest here are university-level rather than student-level outcomes. Therefore, we do not employ student cohorts as in the previous estimations. Instead, we define two time periods for each university surrounding a Cinderella event. The *pre-event* period includes academic years ending three, two, or one year prior to the event, as well as the academic year of the Cinderella event. For instance, if a Cinderella event occurred during the 2007 academic year (spanning fall 2007 to summer 2008), then the *pre-event* period comprises academic years 2004 (fall 2004 to summer 2005), 2005, 2006, and 2007. The *post-event* period consists of academic years ending up to four years following the event (e.g., 2008–2011 in this example). The post-period corresponds to the time when both the freshman and Cinderella cohorts are enrolled in college.

In Equation (4), $Y_{i,t}$ denotes outcomes of university i in year t. The variable $Treated_i$ is an indicator equal to one for treated universities that unexpectedly win a bowl game, and $Post_t$ is an indicator for the post-event period. The pre-event period serves as a baseline because it precedes any potential influence of the Cinderella event (the treatment effect). The coefficient β measures how university outcomes change after the event relative to the *pre-event* period, comparing treated universities with the control universities (those experiencing unexpected losses). This comparison again forms a difference-in-differences framework. Standard errors are clustered at the university level to account for serial correlation and at the year level to account for cross-sectional correlation.

Table 7 presents the results for low-ranked universities. Column (1) examines the number of applications to a university.[14] It shows that the number of applications at treated universities following the Cinderella event does not change significantly, relative to the control. Columns (2) and (3) show no significant changes in acceptance rates or admission yields. Columns (4) and (5) show no significant changes in SAT scores, suggesting that admitted students at the treated schools are not less academically prepared.

[Insert Table 7 here.]

In the Online Appendix Table A3, we report the Cinderella effects on application outcomes for middle and high-ranked universities. We find that only high-ranked universities become more selective following athletic success. As shown in Table A3 Panel B, the number of applications at treated universities post-event increases by 5.5 percent, though not significantly. The acceptance rate decreases by 3.2 percent, and the admission yield increases by 1.5 percent. The admitted

[14] Results are robust using the Poisson Pseudo-Maximum Likelihood estimation.

students, however, do not appear to be less academically prepared, as indicated by the insignificant coefficients for SAT scores in columns (4) and (5).

[Insert Table 8 here.]

Next, we examine whether Cinderella events affect universities' financial conditions: revenue and expenditure. Table 8 presents the results for low-ranked schools. Table 8 Panel A shows no evidence that Cinderella events significantly affect universities' revenues. Across various revenue categories, treated universities exhibit no significant changes relative to the control group following the events. Table 8 Panel B reports the results for university expenditures. Spending across different categories also remains unchanged for treated universities after Cinderella events, except for a decrease in expenditures on public services. These estimates are also economically insignificant. For instance, in Table 8 Panel A, based on column (6), total revenue for treated schools increases by 0.1%.

We also examine whether Cinderella events influence revenues and expenditures for middle-ranked and high-ranked schools. Table A4 shows that high-ranked schools experience an increase in total revenue following Cinderella events, along with higher expenditures on scholarships. These changes may help explain the observed improvement in earnings outcomes among students at high-ranked schools.

Overall, the evidence suggests that low-ranked universities do not benefit from the advertising effects of athletic success in terms of increasing their applicant pools or generating higher revenues. Therefore, the adverse Cinderella effects on student default and earnings outcomes are unlikely to stem from universities' admission policies or financial strain following the events. In contrast, we find suggestive evidence that high-ranked schools may benefit from the publicity generated by athletic success, leading to improved earnings outcomes for their students.

5 Conclusion

This paper provides evidence that unexpected intercollegiate athletic success can disrupt human capital development among students at universities and adversely affect their financial outcomes after graduation. We find that following unexpected college football bowl game victories, incumbent and incoming students at low-ranked universities are more likely to default on their student loans and earn lower salaries after graduation, potentially reflecting a shift in student preferences away from academic effort toward athletics-oriented activities.An alternative identification strategy based on bowl game appearances further corroborates these findings.

Moreover, we find no evidence that such effects are driven by peer effects – where athletic success attracts less academically focused students who negatively influence their peers, or by the resource constraint hypothesis – which suggests that a surge in applications and admissions could strain university resources, diminish educational quality, and lead to poorer student outcomes.

Overall, these results highlight how preferences shaped by athletic success can influence human capital development, distinct from the commonly emphasized assortative matching between students and universities. The findings imply that university activities and campus sentiment meaningfully affect student educational and financial trajectories independently of selection effects.

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Figure 1. The Cinderella effect on student loan default risk

This figure plots the estimates of β coefficients from the following OLS regression: $Cohort\ Default\ Rate\ \%_{i,c} = \sum_{c=1}^{9} \beta_c Cohort_s \times Treated_i + \sum_{c=1}^{9} \delta_s Cohort_c + \gamma_i Treated_i + University\ FE + Game\ Pair \times Year\ FE + \epsilon_{i,c}$, where i indexes schools and c indexes student cohorts. $Treated_i$ is an indicator equal to one for schools that unexpectedly win a bowl game. $Cohort_c$ includes indicators for nine student cohorts: alumni cohorts who graduate one to three years before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The cohort default rate for the most recent graduates serves as the baseline. The red, green, and blue lines represent estimated changes in default rates for low-ranked, middle-ranked, and high-ranked schools, respectively. Standard errors are two-way clustered at the school and year levels. The bars surrounding each coefficient represent the 5% and 95% confidence intervals.

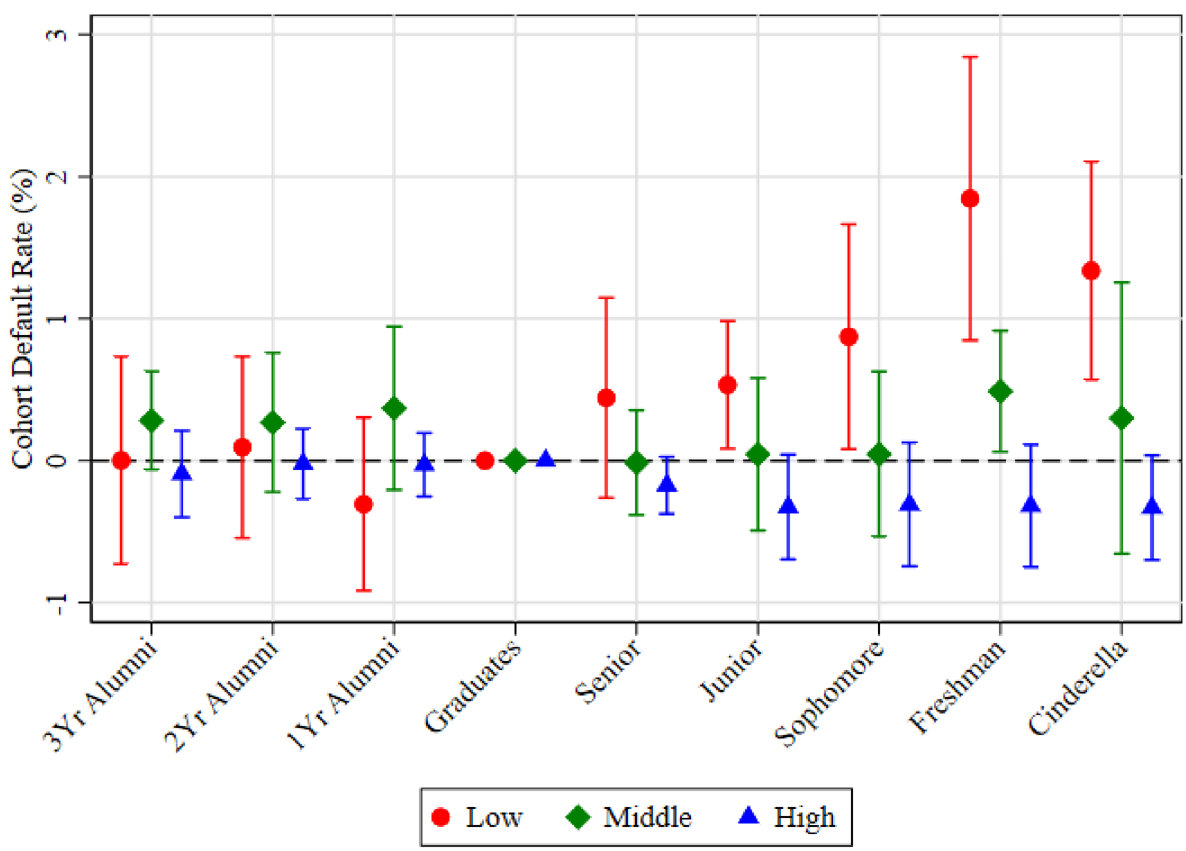


Figure 2. The Cinderella effect on short-term labor market outcomes

This figure plots the estimates of β coefficients from the following OLS regression: $Log(Avg.\ Salary\ (Year\ 0\ to\ Year\ 3)^{u}_{i,c}) = \sum_{c=1}^{9} \beta_c Cohort_c \times Treated_i + \sum_{c=1}^{9} \delta_c Cohort_c + \gamma_i Treated_i + University\ FE + Game\ Pair \times Year\ FE + \epsilon^{u}_{i,c}$, where i indexes universities, c cohorts, and u individuals. $Treated_i$ is an indicator equal to one for schools that unexpectedly win a bowl game. $Cohort_c$ includes indicators for nine student cohorts: alumni cohorts who graduate one to three years before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The earnings for the most recent graduates serve as the baseline. The red, green, and blue lines plot the estimated changes in earnings for low-ranked, middle-ranked, and high-ranked schools, respectively. Standard errors are two-way clustered at the school and year levels. The bars surrounding each coefficient represent the 5% and 95% confidence intervals.

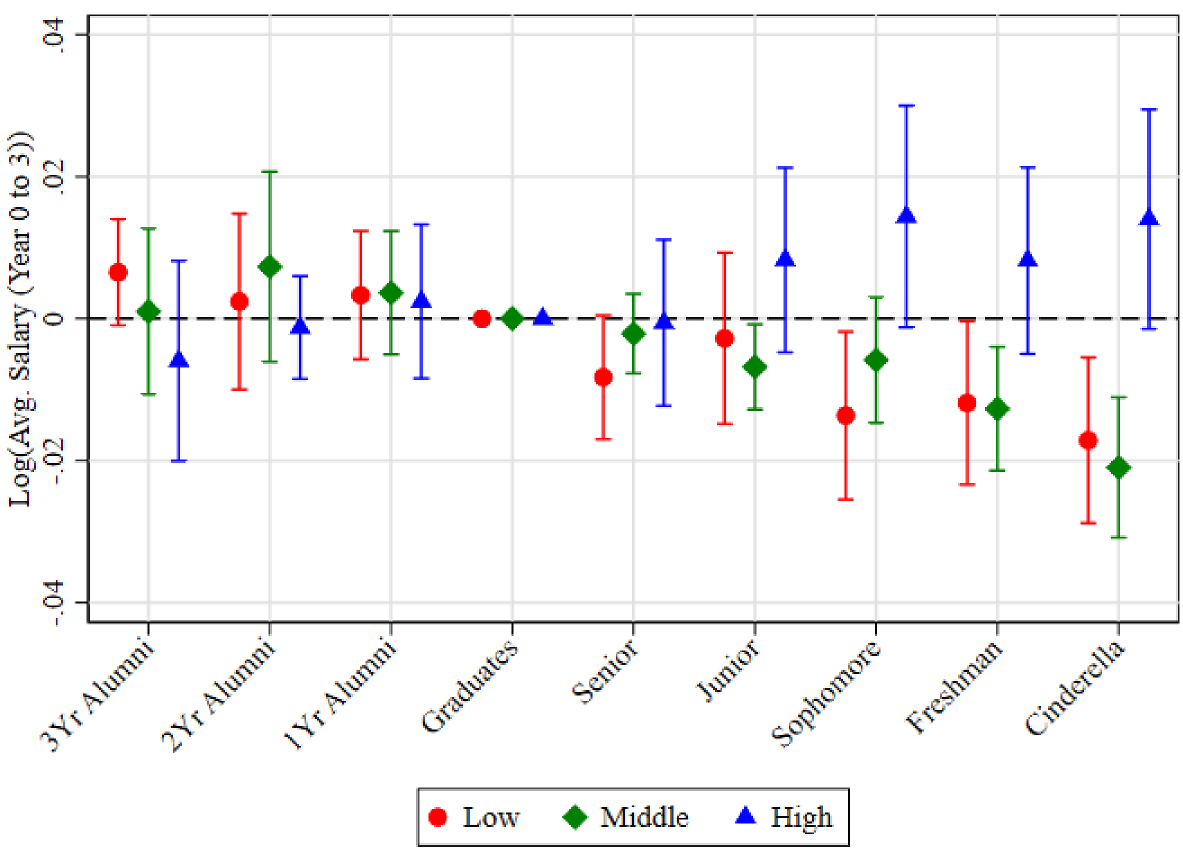


Figure 3. The Cinderella effect on long-term labor market outcomes

This figure plots the estimates of β coefficients from the following OLS regression: $Log(Avg.\ Salary\ (Year\ 4\ to\ Year\ 6)^{u}_{i,c}) = \sum_{c=1}^{9} \beta_c \mathit{Cohort}_c \times Treated_i + \sum_{c=1}^{9} \delta_c Cohort_c + \gamma_i Treated_i + University\ FE + Game\ Pair \times Year\ FE + \epsilon^{u}_{i,c}$, where i indexes universities, c cohorts, and u individuals. $Treated_i$ is an indicator equal to one for schools that unexpectedly win a bowl game. $Cohort_c$ includes indicators for nine student cohorts: alumni cohorts who graduate one to three years before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The earnings for the most recent graduates serve as the baseline. The red, green, and blue lines plot the estimated changes in earnings for low-ranked, middle-ranked, and high-ranked schools, respectively. Standard errors are two-way clustered at the school and year levels. The bars surrounding each coefficient represent the 5% and 95% confidence intervals.

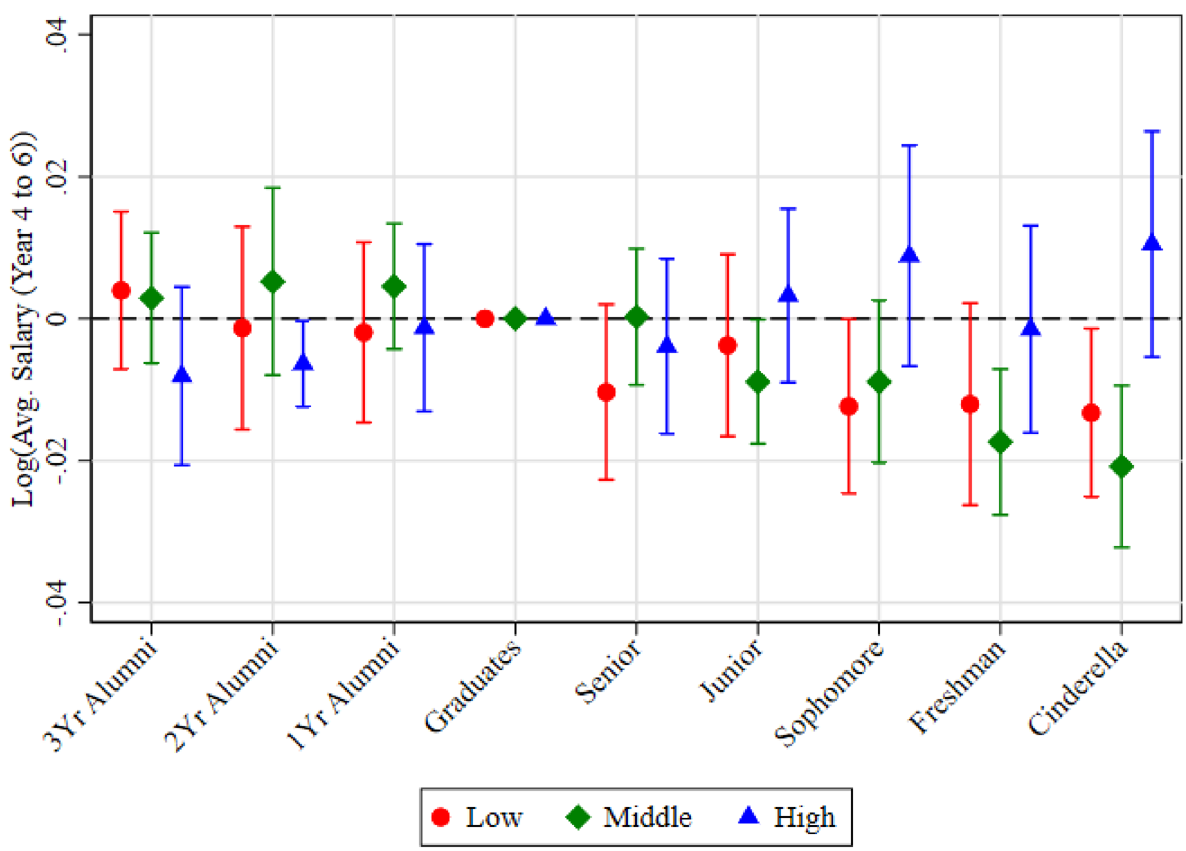
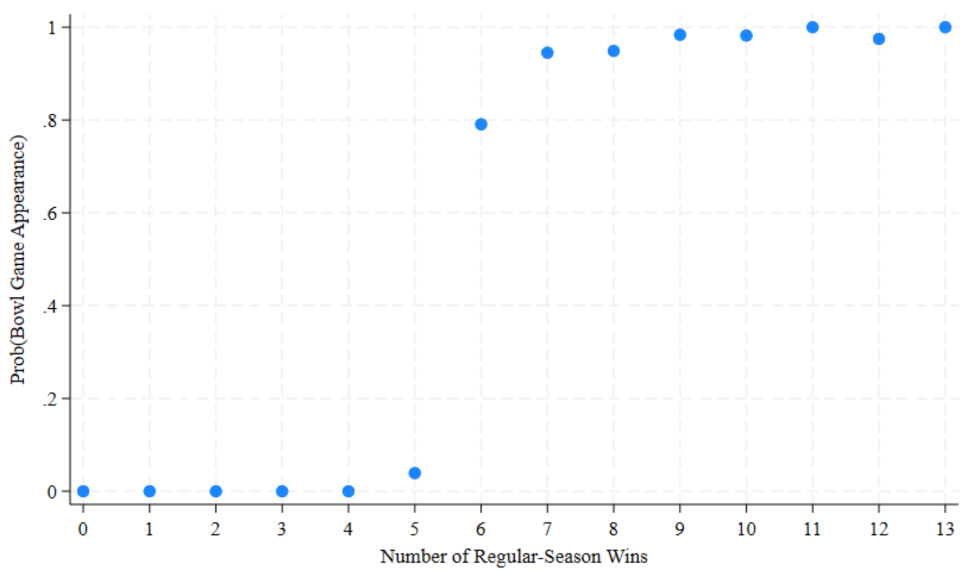


Figure 4. Regular-season wins and bowl game eligibility

This figure shows regular-season winning records and bowl game eligibility. The x-axis represents the number of regular-season wins, and the y-axis indicates the percentage of schools that appeared in a bowl game. The sample covers 2002 to 2019. Panel A includes seasons with 11 regular-season games and periods when the NCAA maintained a lower eligibility threshold (i.e., 2004, 2005, and 2010 onward). Panel B includes seasons with 12 games and stricter eligibility standards (2002, 2003, and 2006–2009).

Panel A: High-six seasons



Panel B: Low-six seasons

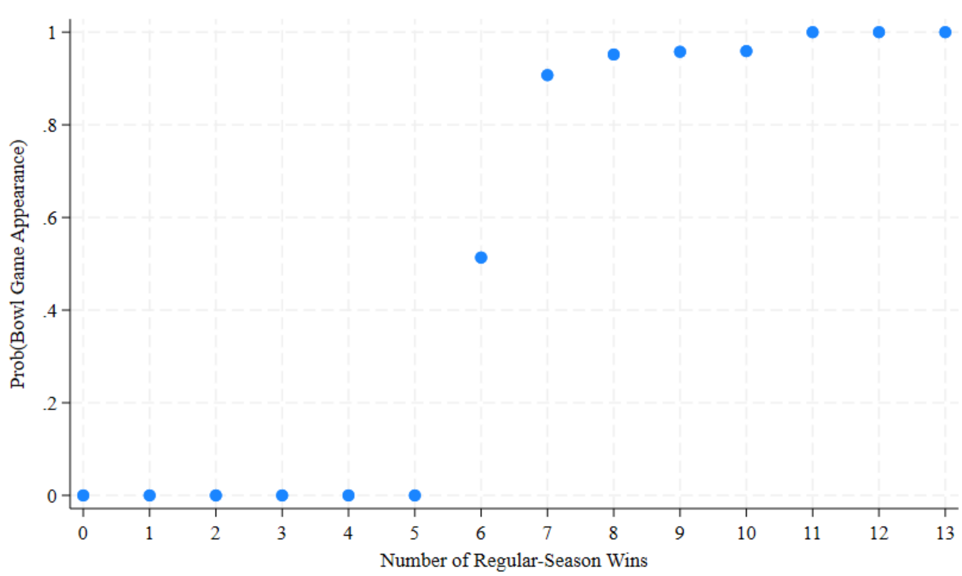


Figure 5. The bowl game effect on student loan default risk in "high-six" seasons

This figure plots the estimates of β coefficients from the following OLS regression: $Cohort\ Default\ Rate\ \%_{i,c} = \sum_{c=1}^{9} \beta_c Cohort_c \times Treated_i + \sum_{c=1}^{9} \delta_c Cohort_c + \gamma_i Treated_i + University\ FE + Game\ Year \times Year\ FE + \epsilon_{i,c}$, where i indexes schools and c indexes student cohorts. The sample includes schools that win five regular-season games and do not appear in bowl games, and those that win six regular-season games in "high-six" seasons. $Treated_i$ is an indicator equal to one for schools that win six regular-season games in "high-six" seasons. $Cohort_c$ includes indicators for nine student cohorts: alumni cohorts who graduate one to three years before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The cohort default rate for the most recent graduates serves as the baseline. The red, green, and blue lines represent estimated changes in default rates for low-ranked, middle-ranked, and high-ranked schools, respectively. Standard errors are two-way clustered at the school and year levels. The bars surrounding each coefficient represent the 5% and 95% confidence intervals.

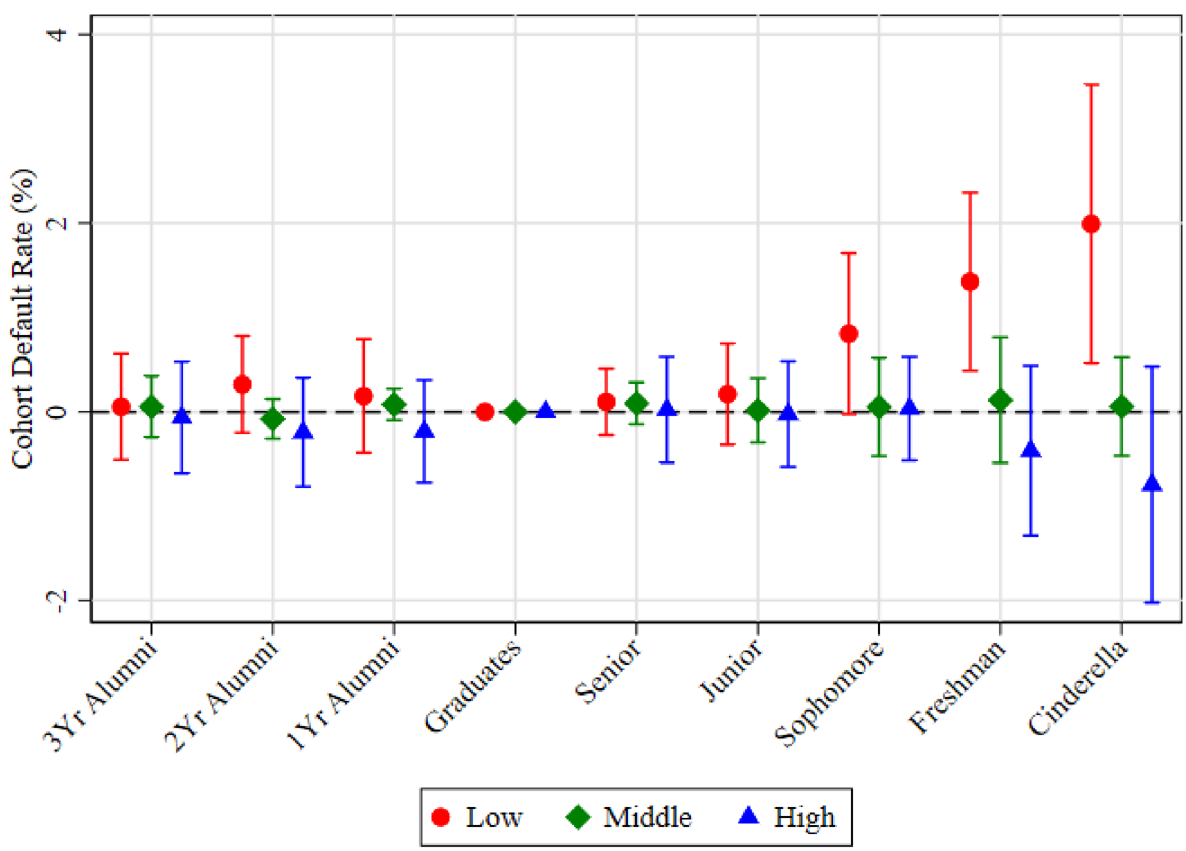
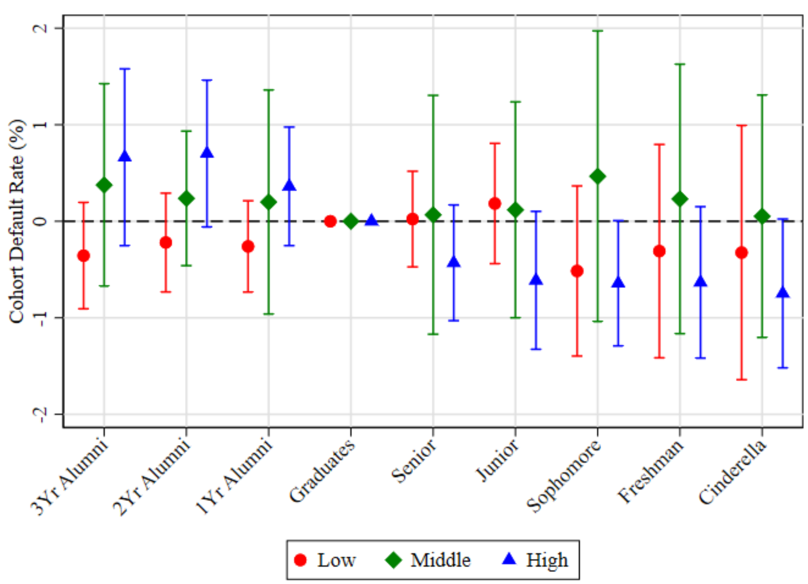


Figure 6. The bowl game effect in "low-six" seasons

This figure plots the estimates of β coefficients from OLS regression: $Y_{i,c} = \sum_{c=1}^{9} \beta_c \boldsymbol{Cohort_c} \times Treated_i + \sum_{c=1}^{9} \delta_c Cohort_c + \gamma_i Treated_i + University\ FE + Game\ Year \times Year\ FE + \epsilon_{i,c}^{u}$, where i indexes universities and c cohorts. The sample includes schools that win five regular-season games and do not appear in bowl games, and those that win six regular-season games in "low-six" seasons. $Treated_i$ is an indicator equal to one for schools that win six regular-season games in "low-six" seasons. $Cohort_c$ includes indicators for nine student cohorts: alumni cohorts who graduate one to three years before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. Panel A shows the bowl game effect on the cohort default rate, and Panel B shows the bowl game effect on short-term labor market outcomes. The cohort default rate or earnings for the most recent graduates serve as the baseline. The red, green, and blue lines plot the estimated changes in earnings for low-ranked, middle-ranked, and high-ranked schools, respectively. Standard errors are two-way clustered at the school and year levels. The bars surrounding each coefficient represent the 5% and 95% confidence intervals.

Panel A. Cohort Default Rate (%)



Panel B. Log(Avg. Salary (Year 0 to 3))

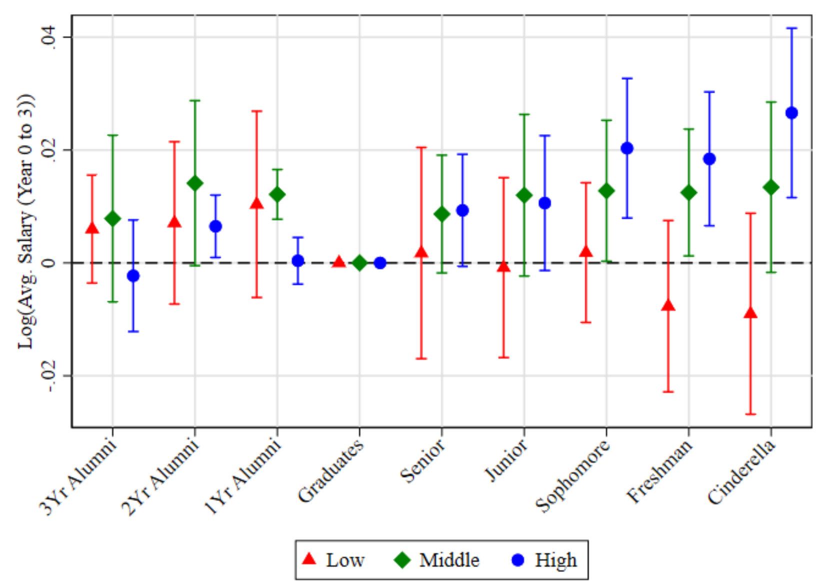


Table 1. Summary statistics

This table provides variable definitions and summary statistics. Panel 1.A reports summary statistics on cohort default rate and post-graduation earnings. *Cohort Default Rate (%)* is the percentage of a university's borrowers who enter repayment on Federal Family Education Loans or Direct Loans in a given year and default within three years after entering repayment. *Years of Undergraduate Study* refers to the number of years a student enrolled in an undergraduate program. *Salary (Year 0, T)* and *Salary (Year 1, T)* represent earnings (in thousands) in the graduation year and the first year after graduation, respectively. *Avg. Salary (Year 0 to 3)* and *Avg. Salary (Year 4 to 6)* denote the average earnings (in thousands) between Year 0 to Year 3 and between Year 4 to Year 6 after graduation, respectively. Panel 1.B reports summary statistics on university characteristics. *Applicants (T)*, *Admitted (T)*, and *Enrolled (T)* are the number of first-time undergraduate applicants, admitted students, and enrollees, respectively, measured in thousands. *Acceptance Rate (%)* is calculated as $Admitted/Applicants \times 100$, and *Admission Yield (%)* as $Enrolled/Admitted \times 100$. *SAT25th* and *SAT75th* are the 25th and 75th percentile SAT scores of enrolled students. *Total Revenue (B)* denotes total university revenue, measured in billions. *Tuition (Revenue, M)* is revenue from all tuition and fees for educational purposes, measured in millions. *Federal (Revenue, M)*, *State (Revenue, M)*, and *Local and Private (Revenue, M)* refer to revenues from federal-level, state-level, and local or private-level grants, contracts, and appropriations, respectively. *Auxiliary (Revenue, M)* refers to revenue from auxiliary enterprises such as residence halls, food services, student health services, intercollegiate athletics, college unions, college stores, and movie theaters. *Total Expense (B)* is the sum of all university expenditures, measured in billions. *Instruction (Expense, M)* is the expense for academic instruction, occupational and vocational instruction, community education, preparatory and adult basic education, and remedial and tutorial instruction conducted by the teaching faculty for the institution's students. *Research (Expense, M)* is the spending on activities organized to produce research outcomes. *Academic (Expense, M)* is the expense associated with activities and services that support the institution's primary missions of instruction, research, and public service. *Public Service (Expense, M)* includes spending on non-instructional services such as advisory services, community outreach, and conferences. *Institute Support (Expense, M)* is the expense associated with administrative and operational services such as management, legal, fiscal, space, HR, and public relations. *Scholarship (Expense, M)* is the spending on scholarships and fellowships. *Auxiliary (Expense, M)* refers to spending related to self-supporting campus services, such as residence halls, food services, student health services, intercollegiate athletics, college unions, college stores, faculty and staff parking, and faculty housing. Panel B presents the distribution of undergraduate majors in the sample. All variables are winsorized at the 1st and 99th percentiles.

Panel 1.A. Cohort default rate and earnings after graduation

Variable	Obs	Mean	Std. dev.	P25	P50	P75
Cohort Default Rate (%)	1,598	4.01	2.63	2.10	3.40	5.20
Years of Undergraduate Study	3,924,509	3.77	1.04	3.00	4.00	4.00
Salary (Year 0, T)	3,006,804	50.17	26.69	32.19	43.11	60.70
Salary (Year 1, T)	3,342,890	55.37	28.53	35.46	48.59	68.15
Salary (Year 2, T)	3,472,697	58.73	29.98	37.66	52.03	72.33
Salary (Year 3, T)	3,458,163	61.99	31.88	39.51	55.06	76.31
Salary (Year 4, T)	3,378,487	65.14	33.85	41.24	57.96	80.19
Salary (Year 5, T)	3,180,786	68.14	35.80	42.79	60.60	83.88
Salary (Year 6, T)	2,587,454	70.96	37.97	44.12	62.80	87.26
Avg. Salary (Year 0 to 3, T)	3,678,412	58.56	28.94	38.26	52.20	71.69
Avg. Salary (Year 4 to 6, T)	3,507,978	67.58	34.49	43.09	60.54	83.11

Panel 1.B. University characteristics

Variable	Obs	Mean	Std. dev.	P25	P50	P75
Applications (T)	1,828	19.65	11.77	10.96	16.87	25.79
Admitted (T)	1,828	10.84	5.07	6.94	10.20	13.99
Enrolled (T)	1,828	4.07	1.70	2.87	3.89	5.14
Acceptance Rate (%)	1,828	62.26	19.25	50.63	64.02	76.91
AdmissionYield (%)	1,828	40.16	12.00	31.75	38.80	46.00
SAT25th	1,718	1,077.03	123.76	990.00	1,070.00	1,160.00
SAT75th	1,718	1,293.63	110.97	1,220.00	1,290.00	1,360.00
Total Revenue (B)	1,895	1.48	1.46	0.61	0.97	1.77
Tuition (Revenue, M)	1,895	295.55	222.85	146.93	235.93	366.99
Federal (Revenue, M)	1,895	206.49	206.78	68.77	134.77	274.62
State (Revenue, M)	1,895	237.39	173.09	109.82	204.06	321.32
Local and Private (Revenue, M)	1,895	130.73	157.15	33.58	69.46	154.83
Auxiliary (Revenue, M)	1,895	125.73	92.53	63.51	105.11	163.50
Total Expense (B)	1,895	1.37	1.33	0.56	0.93	1.61
Instruction (Expense, M)	1,895	349.69	282.40	174.40	265.30	384.37
Research (Expense, M)	1,895	233.82	237.99	54.64	162.92	311.23
Academic (Expense, M)	1,895	101.76	95.85	43.10	72.03	114.82
Public Service (Expense, M)	1,895	76.51	98.46	15.06	51.93	96.55
Institute Support (Expense, M)	1,895	84.85	68.56	40.43	64.81	101.67
Scholarship (Expense, M)	1,895	34.28	32.27	13.57	24.88	43.64
Auxiliary (Expense, M)	1,895	136.55	100.34	75.54	112.80	179.88

Table 2. The Cinderella effect on student loan default rates

This table reports the estimates of β coefficients from OLS regression: $Cohort\ Default\ Rate\ \%_{i,c} = \sum_{c=1}^{6} \beta_c \boldsymbol{Cohort_c} \times Treated_i + \sum_{c=1}^{6} \delta_c Cohort_c + \gamma_i Treated_i + Fixed\ effects + \epsilon_{i,c}$, where i indexes schools and c indexes student cohorts. $Treated_i$ is an indicator equal to one for schools that unexpectedly win a bowl game. $Cohort_c$ includes indicators for six student cohorts: alumni cohorts who graduate before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The default rate for students who graduate before the Cinderella events serves as the baseline. Column (1) and Column (2), Column (3) and Column (4), and Column (5) and Column (6) report the effects of athletic success for low-ranked, middle-ranked, and high-ranked schools, respectively. The standard errors are two-way clustered at the school and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Low	Low	Middle	Middle	High	High
Dept. Variable:	Cohort Default Rate (%)					
Graduates and Alumni×Treated	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Senior×Treated	0.218	0.495	-0.239	-0.244	-0.099	-0.137
	(0.311)	(0.333)	(0.199)	(0.201)	(0.169)	(0.083)
Junior×Treated	0.224	0.587	-0.259	-0.186	-0.184	-0.290**
	(0.325)	(0.339)	(0.161)	(0.229)	(0.128)	(0.135)
Sophomore×Treated	0.623	0.925**	-0.265	-0.184	-0.191	-0.272
	(0.382)	(0.395)	(0.247)	(0.263)	(0.183)	(0.168)
Freshman×Treated	1.238***	1.897***	0.206	0.258	-0.050	-0.282
	(0.337)	(0.503)	(0.258)	(0.213)	(0.216)	(0.164)
Cinderella×Treated	1.059***	1.390***	0.048	0.070	-0.237	-0.295
	(0.364)	(0.319)	(0.443)	(0.458)	(0.196)	(0.178)
Year FE	Yes	No	Yes	No	Yes	No
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Game Pair×Year FE	No	Yes	No	Yes	No	Yes
Observations	990	380	1,131	666	1,071	546
R-squared	0.922	0.961	0.889	0.941	0.916	0.973

Table 3. The Cinderella effect on short-term labor market outcomes

This table reports the estimates of β coefficients from OLS regression: $Log(Avg.\ Salary\ (Year\ 0\ to\ Year\ 3)^{u}_{i,c}) = \sum_{c=1}^{6} \beta_c \boldsymbol{Cohort}_c \times Treated_i + \sum_{c=1}^{6} \delta_c Cohort_c + \gamma_i Treated_i + Fixed\ effects + \epsilon^{u}_{i,c}$, where i indexes universities, c cohorts, and u individuals. $Treated_i$ is an indicator equal to one for schools that unexpectedly win a bowl game. $Cohort_c$ includes indicators for six student cohorts: alumni cohorts who graduate before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The earnings for students who graduate before the Cinderella events serve as the baseline. Column (1) and Column (2), Column (3) and Column (4), and Column (5) and Column (6) report the effects of athletic success for low-ranked, middle-ranked, and high-ranked schools, respectively. The standard errors are two-way clustered at the school and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Low	Low	Middle	Middle	High	High
Dept. Variable:	Log(Avg. Salary (Year 0 to 3))					
Graduates and Alumni×Treated	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Senior×Treated	-0.011**	-0.015**	-0.005	-0.003	0.000	0.003
	(0.004)	(0.005)	(0.003)	(0.005)	(0.005)	(0.006)
Junior×Treated	-0.006	-0.014*	-0.010**	-0.013	0.009	0.005
	(0.006)	(0.008)	(0.005)	(0.008)	(0.006)	(0.007)
Sophomore×Treated	-0.017**	-0.027***	-0.009*	0.000	0.015*	0.023***
	(0.006)	(0.008)	(0.005)	(0.006)	(0.008)	(0.007)
Freshman×Treated	-0.015**	-0.020**	-0.016**	-0.017**	0.009	0.007
	(0.005)	(0.008)	(0.006)	(0.007)	(0.006)	(0.007)
Cinderella×Treated	-0.020***	-0.021**	-0.024***	-0.028***	0.015**	0.014*
	(0.006)	(0.008)	(0.005)	(0.005)	(0.007)	(0.008)
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Game Pair×Year FE	Yes	No	Yes	No	Yes	No
Game Pair×Year×Major FE	No	Yes	No	Yes	No	Yes
Observations	758,302	352,162	1,461,851	708,117	1,458,259	704,941
R-squared	0.030	0.114	0.032	0.113	0.046	0.127

Table 4. The Cinderella effect on long-term labor market outcomes

This table reports the estimates of β coefficients from OLS regression: $Log(Avg.\ Salary\ (Year\ 4\ to\ Year\ 6)^{u}_{i,c}) = \sum_{c=1}^{6} \beta_c \boldsymbol{Cohort_c} \times Treated_i + \sum_{c=1}^{6} \delta_c Cohort_c + \gamma_i Treated_i + Fixed\ effects + \epsilon^{u}_{i,c}$, where i indexes universities, c cohorts, and u individuals. $Treated_i$ is an indicator equal to one for schools that unexpectedly win a bowl game. $Cohort_c$ includes indicators for six student cohorts: alumni cohorts who graduate before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The earnings for students who graduate before the Cinderella events serve as the baseline. Column (1) and Column (2), Column (3) and Column (4), and Column (5) and Column (6) report the effects of athletic success for low-ranked, middle-ranked, and high-ranked schools, respectively. The standard errors are two-way clustered at the school and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Low	Low	Middle	Middle	High	High
Dept. Variable:	Log(Avg. Salary (Year 4 to 6))					
Graduates and Alumni × Treated	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Senior×Treated	-0.010	-0.012*	-0.003	0.002	-0.000	0.002
	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)	(0.007)
Junior×Treated	-0.004	-0.014	-0.012**	-0.013*	0.007	0.001
	(0.006)	(0.008)	(0.004)	(0.007)	(0.006)	(0.007)
Sophomore×Treated	-0.012**	-0.028***	-0.012**	-0.005	0.013*	0.020**
	(0.005)	(0.007)	(0.005)	(0.007)	(0.007)	(0.009)
Freshman×Treated	-0.012*	-0.015*	-0.020***	-0.023**	0.002	-0.001
	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)	(0.009)
Cinderella×Treated	-0.013*	-0.016*	-0.024***	-0.024***	0.014*	0.016
	(0.007)	(0.009)	(0.005)	(0.007)	(0.007)	(0.010)
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×Game Pair FE	Yes	No	Yes	No	Yes	No
Year×Game Pair×Major FE	No	Yes	No	Yes	No	Yes
Observations	713,568	324,597	1,409,258	671,420	1,385,152	656,185
R-squared	0.032	0.103	0.026	0.092	0.039	0.103

Table 5. The bowl game effect on student loan default rates in "high-six" seasons

This table reports the estimates of β coefficients from OLS regression: $Cohort\ Default\ Rate\ \%_{i,c} = \sum_{c=1}^{6} \beta_c \boldsymbol{Cohort}_c \times Treated_i + \sum_{c=1}^{6} \delta_c Cohort_c + \gamma_i Treated_i + Fixed\ effects + \epsilon_{i,c}$, where i indexes schools and c indexes student cohorts. The sample includes schools that win five regular-season games and do not appear in bowl games, and those that win six regular-season games in "high-six" seasons. $Treated_i$ is an indicator equal to one for schools that win six regular-season games in "high-six" seasons. $Cohort_c$ includes indicators for six student cohorts: alumni cohorts who graduate before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The default rate for students who graduate before the Cinderella events serves as the baseline. Column (1) and Column (2), Column (3) and Column (4), and Column (5) and Column (6) report the effects of athletic success for low-ranked, middle-ranked, and high-ranked schools, respectively. The standard errors are two-way clustered at the school and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Low	Low	Middle	Middle	High	High
Dept. Variable:	Cohort Default Rate (%)					
Graduates and Alumni×Treated	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Senior×Treated	-0.036	-0.026	0.075	0.076	0.133	0.145
	(0.202)	(0.178)	(0.156)	(0.155)	(0.264)	(0.261)
Junior×Treated	0.001	0.058	-0.020	0.001	0.083	0.099
	(0.247)	(0.253)	(0.181)	(0.184)	(0.222)	(0.232)
Sophomore×Treated	0.655*	0.698*	0.006	0.037	0.160	0.158
	(0.369)	(0.389)	(0.270)	(0.281)	(0.219)	(0.227)
Freshman×Treated	1.185**	1.250***	0.096	0.109	-0.271	-0.289
	(0.405)	(0.413)	(0.315)	(0.321)	(0.328)	(0.357)
Cinderella×Treated	1.807***	1.861***	0.039	0.042	-0.591	-0.650
	(0.587)	(0.592)	(0.241)	(0.256)	(0.445)	(0.477)
Year FE	Yes	No	Yes	No	Yes	No
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Game Year×Year FE	No	Yes	No	Yes	No	Yes
Observations	1,240	1,240	1,269	1,269	1,300	1,300
R-squared	0.892	0.897	0.898	0.902	0.912	0.914

Table 6. Ruling out the peer effect channel

This table reports the estimates of β coefficients from OLS regression: $Log(Avg.\ Salary\ (Year\ 0\ to\ Year\ 3)^{u}_{i,c}) = \beta_c Freshman_c \times Treated_i + \delta_c Freshman_c + \gamma_i Treated_i + Fixed\ effects + \epsilon^{u}_{i,c}$, where i indexes universities, c cohorts, and u individuals. The sample includes two groups: freshman cohorts who take four years to graduate and junior cohorts who take six years to graduate. $Freshman_c$ is an indicator equal to one for the freshman cohort. The earnings for the junior cohort serve as the baseline. The standard errors are two-way clustered at the school and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Sample:	Low	
Dept. Variable:	Log(Avg. Salary (Year 0 to 3))	
Junior×Treated	Baseline	Baseline
Freshman×Treated	0.025	-0.004
	(0.025)	(0.030)
University FE	Yes	Yes
Year×Game Pair FE	Yes	No
Year×Game Pair×Major FE	No	Yes
Observations	43,800	20,483
R-squared	0.042	0.154

Table 7. The Cinderella effect on universities' applications

This table reports the estimates of β coefficients from the following specification: $Y_{i,t} = \beta_s Treated_i \times Post_t + \delta_t Post_t + \gamma_i Treated_i + Fixed\,effects + \epsilon_{i,t}$, where i indexes universities and t indexes years. $Y_{i,t}$ is one of the number of applications, acceptance rate, admission yield, 25th percentile SAT score, and 75th percentile SAT score. The model uses data for the three years preceding the event, the event year, and four subsequent years. The variable $Treated_i$ is an indicator equal to one for treated universities that unexpectedly win a bowl game, and $Post_t$ is an indicator for the post-event period. The standard errors are two-way clustered at the school and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Sample:	Low				
Dept. Variable:	Log(Applications)	Acceptance Rate (%)	Admission Yield (%)	SAT25th	SAT75th
Treated×Post	0.013	-0.869	-0.546	-0.796	-5.064
	(0.029)	(1.330)	(0.934)	(4.207)	(4.752)
University FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,051	1,051	1,051	985	985
R-squared	0.966	0.886	0.803	0.970	0.962

Table 8. The Cinderella effect on universities' financials

This table reports the estimates of β coefficients from Poisson pseudo-maximum likelihood regression: $Y_{i,t} = \beta_s Treated_i \times Post_t + \delta_t Post_t + \gamma_i Treated_i + Fixed\ effects + \epsilon_{i,t}$, where $Y_{i,t}$ denotes the revenue or expenditure of university i in year t. The model uses data for the three years preceding the event, the event year, and four subsequent years. The variable $Treated_i$ is an indicator equal to one for treated universities that unexpectedly win a bowl game, and $Post_t$ is an indicator for the post-event period. The standard errors are two-way clustered at the school and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel 8.A: Revenue

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Low					
Dept. Variable:	Tuition	Federal	State	Local and Private	Auxiliary	Total Revenue
Treated×Post	-0.052	-0.014	0.029	-0.060	-0.030	0.001
	(0.035)	(0.029)	(0.034)	(0.056)	(0.032)	(0.024)
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,090	1,090	1,090	1,090	1,090	1,090
Pseudo R-squared	0.986	0.991	0.979	0.978	0.961	0.990

Panel 8.B: Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	Low							
Dept. Variable:	Instruction	Research	Academic	Public Service	Institute Support	Scholarship	Auxiliary	Total Expense
Treated×Post	-0.025	-0.025	0.016	-0.113*	-0.028	-0.015	0.004	-0.026
	(0.031)	(0.045)	(0.030)	(0.062)	(0.040)	(0.092)	(0.030)	(0.024)
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,090	1,090	1,090	1,074	1,090	1,023	1,090	1,090
Pseudo R-squared	0.991	0.991	0.981	0.962	0.967	0.919	0.972	0.995

Online Appendix for

Student Debt and the Cinderella Effect

Appendix A Additional Tables and Figures

Figure A1. The average cohort default rate

This figure plots the average cohort default rate for different student cohorts: alumni cohorts who graduate one to three years before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The red dots represent the average cohort default rate for low-ranked treated schools, and the blue dots represent the average default rate for corresponding control schools.

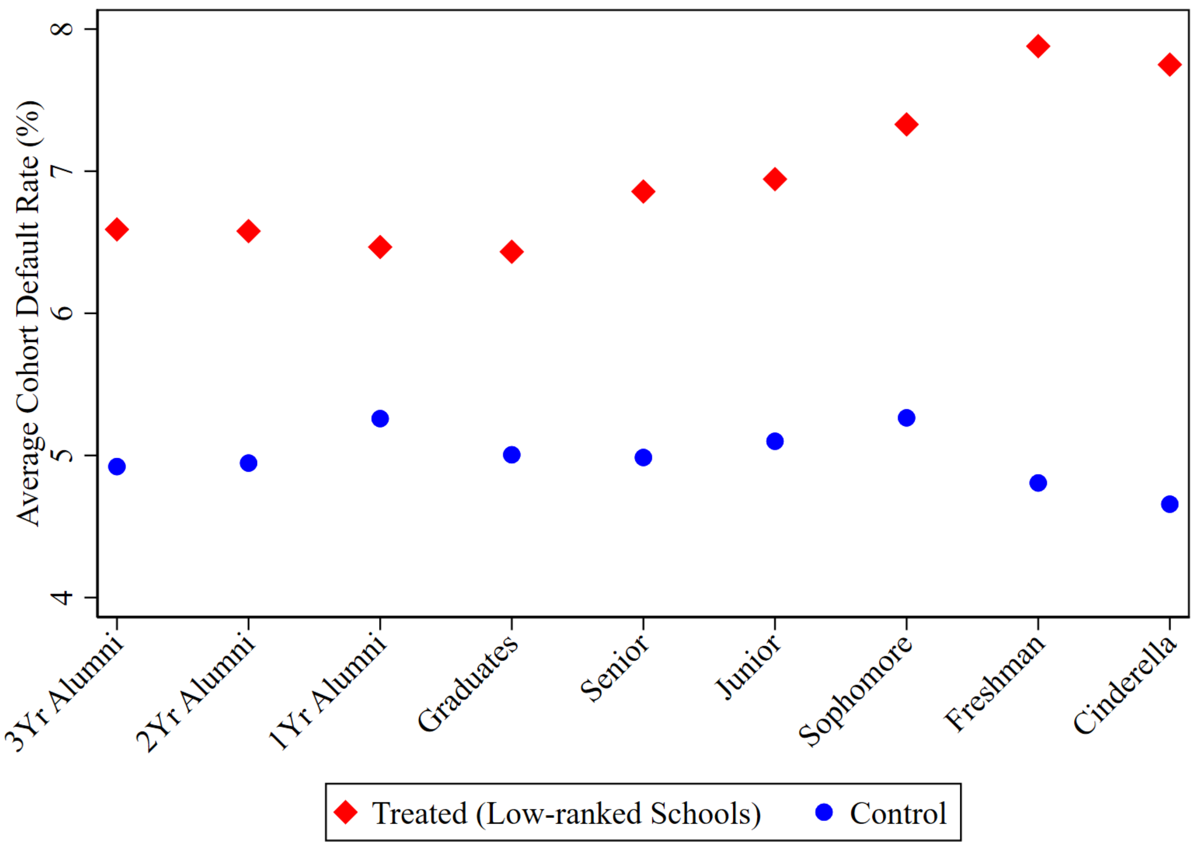


Figure A2. The bowl game effect on short-term labor market outcomes in "high-six" seasons

This figure plots the estimates of β coefficients from OLS regression: $Log(Avg.\ Salary\ (Year\ 0\ to\ Year\ 3)^{u}_{i,c}) = \sum_{c=1}^{9} \beta_c \boldsymbol{Cohort_c} \times Treated_i + \sum_{c=1}^{9} \delta_c Cohort_c + \gamma_i Treated_i + University\ FE + Game\ Year \times Year\ FE + \epsilon^{u}_{i,c}$, where i indexes universities, c cohorts, and u individuals. The sample includes schools that win five regular-season games and do not appear in bowl games, and those that win six regular-season games in "high-six" seasons. $Treated_i$ is an indicator equal to one for schools that win six regular-season games in "high-six" seasons. $Cohort_c$ includes indicators for nine student cohorts: alumni cohorts who graduate one to three years before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The earnings for the most recent graduates serve as the baseline. The red, green, and blue lines plot the estimated changes in earnings for low-ranked, middle-ranked, and high-ranked schools, respectively. Standard errors are two-way clustered at the school and year levels. The bars surrounding each coefficient represent the 5% and 95% confidence intervals.

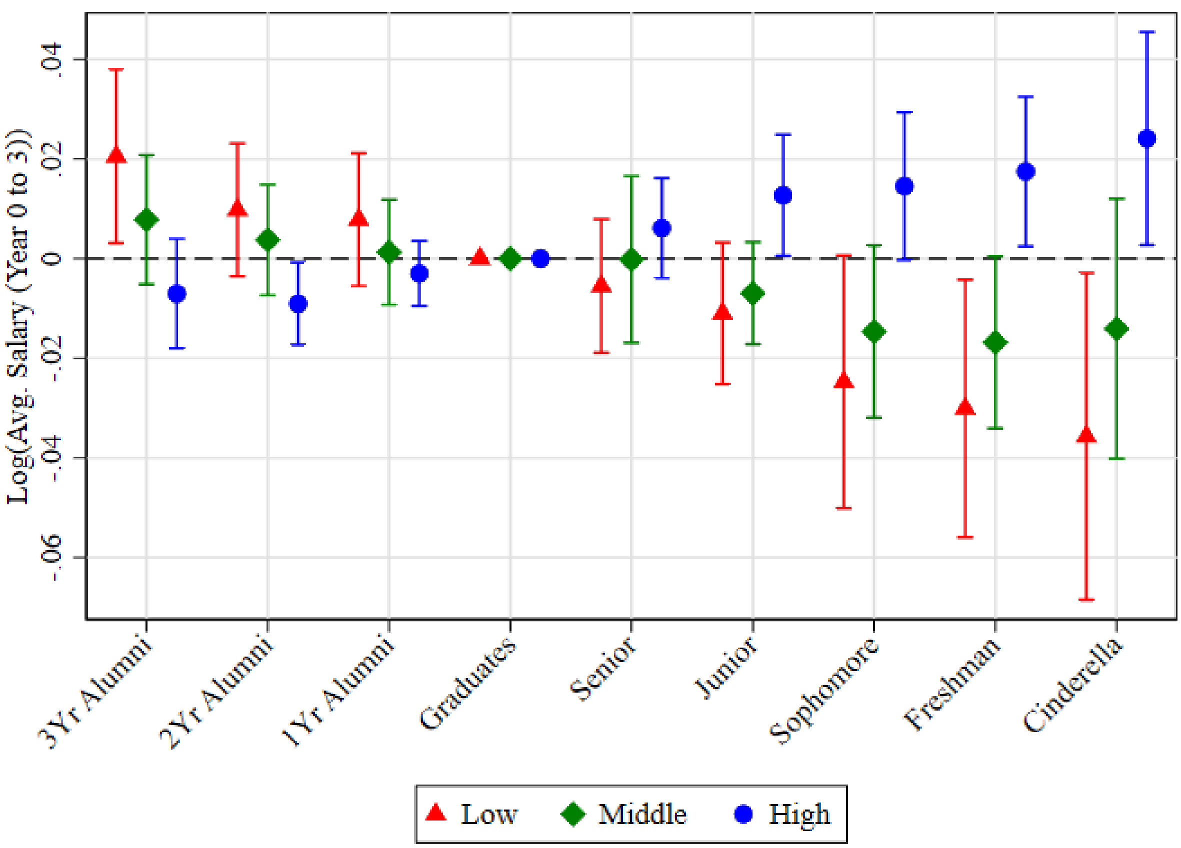


Table A1. Cinderella Event and the Treated and Control Universities

This table lists the date of the 122 Cinderella events, along with the treated and control universities in each event. It also reports the treated universities' U.S. News ranking in 2002 (or the 2025 ranking if 2002 data are unavailable), Forbes ranking in 2025, and the ranking group (low, middle, or high).

Nr.	Event Date	Treated School	US News(Forbes)	Group	Control School
1	12/17/2002	University of North Texas	220(209)	Low	University of Cincinnati
2	12/25/2002	Tulane University of Louisiana	46(147)	High	University of Hawaii at Manoa
3	12/27/2002	University of Mississippi	171(217)	Middle	University of Nebraska
4	12/28/2002	University of Wisconsin	32(50)	High	University of Colorado Boulder
5	12/28/2002	University of Virginia	24(34)	High	West Virginia University
6	12/31/2002	California State University	179(185)	Middle	Georgia Institute of Technology
7	1/1/2003	University of Georgia	46(62)	High	Florida State University
8	1/1/2003	University of Oklahoma	132(113)	Middle	Washington State University
9	1/1/2003	Auburn University	105(117)	Middle	Penn State University
10	1/3/2003	Ohio State University	41(86)	High	University of Miami
11	1/1/2004	University of Iowa	98(155)	Middle	University of Florida
12	1/2/2004	Clemson University	80(98)	High	The University of Tennessee
13	1/2/2004	Ohio State University	41(86)	High	Kansas State University
14	1/4/2004	Louisiana State University	179(139)	Middle	University of Oklahoma
15	12/23/2004	University of Wyoming	220(189)	Low	University of California
16	12/27/2004	California State University	179(185)	Middle	University of Virginia
17	12/30/2004	Texas Tech University	214(205)	Low	University of California
18	12/30/2004	Boston College	38(59)	High	UNC
19	12/31/2004	Arizona State University	121(109)	Middle	Purdue University
20	1/1/2005	University of Iowa	98(155)	Middle	Louisiana State University
21	1/1/2005	The University of Tennessee	109(142)	Middle	Texas A & M University
22	12/28/2005	University of Nebraska	152(191)	Middle	University of Michigan
23	12/29/2005	University of Utah	136(94)	Middle	Georgia Institute of Technology
24	12/30/2005	Louisiana State University	179(139)	Middle	University of Miami
25	12/30/2005	University of Virginia	24(34)	High	University of Minnesota
26	12/31/2005	University of Tulsa	179(307)	Middle	California State University
27	1/2/2006	University of Wisconsin	32(50)	High	Auburn University
28	1/2/2006	West Virginia University	220(236)	Low	University of Georgia
29	1/4/2006	The University of Texas at Austin	48(46)	High	University of Southern California
30	12/22/2006	Troy University	.(.)	Low	Rice University
31	12/29/2006	University of Kentucky	152(160)	Middle	Clemson University
32	1/1/2007	Boise State University	296(353)	Low	University of Oklahoma
33	1/1/2007	Penn State University	46(196)	High	The University of Tennessee
34	1/6/2007	University of Florida	30(26)	High	Ohio State University
35	12/23/2007	East Carolina University	189(313)	Low	Boise State University
36	12/31/2007	University of Oregon	109(148)	Middle	University of South Florida
37	12/31/2007	California State University	179(185)	Middle	Georgia Institute of Technology
38	1/1/2008	University of Michigan	25(29)	High	University of Florida
39	1/2/2008	West Virginia University	220(236)	Low	University of Oklahoma
40	12/21/2008	University of Southern Mississippi	342(.)	Low	Troy University

Table A1. Cinderella Event and the Treated and Control Universities

Nr.	Event Date	Treated School	US News(Forbes)	Group	Control School
41	12/26/2008	Florida Atlantic University	189(188)	Low	Central Michigan University
42	12/31/2008	Louisiana State University	179(139)	Middle	Georgia Institute of Technology
43	12/31/2008	Vanderbilt University	21(15)	High	Boston College
44	1/2/2009	University of Utah	136(94)	Middle	The University of Alabama
45	1/2/2009	University of Mississippi	171(217)	Middle	Texas Tech University
46	12/19/2009	University of Wyoming	220(189)	Low	California State University
47	12/24/2009	Southern Methodist University	91(99)	Middle	University of Nevada
48	1/1/2010	Ohio State University	41(86)	High	University of Oregon
49	1/2/2010	University of Connecticut	70(85)	High	University of South Carolina
50	1/4/2010	Boise State University	296(353)	Low	Texas Christian University
51	1/5/2010	University of Iowa	98(155)	Middle	Georgia Institute of Technology
52	12/24/2010	University of Tulsa	179(307)	Middle	University of Hawaii at Manoa
53	12/30/2010	University of Washington	45(44)	High	University of Nebraska
54	12/31/2010	University of Central Florida	121(110)	Middle	University of Georgia
55	12/31/2010	University of South Florida	91(107)	Middle	Clemson University
56	12/17/2011	University of Louisiana at Lafayette	377(.)	Low	San Diego State University
57	12/20/2011	Marshall University	315(.)	Low	Florida International University
58	12/24/2012	Southern Methodist University	91(99)	Middle	California State University
59	12/26/2012	Central Michigan University	259(408)	Low	Western Kentucky University
60	12/28/2012	Ohio University	179(.)	Middle	University of Louisiana at Monroe
61	12/29/2012	Syracuse University	73(108)	High	West Virginia University
62	12/31/2012	Clemson University	80(98)	High	Louisiana State University
63	12/31/2012	Georgia Institute of Technology	41(38)	High	University of Southern California
64	1/2/2013	University of Louisville	179(252)	Middle	University of Florida
65	12/21/2013	Colorado State University	148(330)	Middle	Washington State University
66	12/26/2013	University of Pittsburgh	70(143)	High	Bowling Green State University
67	12/30/2013	Texas Tech University	214(205)	Low	Arizona State University
68	1/1/2014	Michigan State University	63(90)	High	Stanford University
69	1/1/2014	University of Central Florida	121(110)	Middle	Baylor University
70	1/1/2014	University of Nebraska	152(191)	Middle	University of Georgia
71	1/2/2014	University of Oklahoma	132(113)	Middle	The University of Alabama
72	1/5/2014	Arkansas State University	342(.)	Low	Ball State University
73	12/29/2014	Clemson University	80(98)	High	University of Oklahoma
74	12/30/2014	University of Notre Dame	19(42)	High	Louisiana State University
75	12/31/2014	Georgia Institute of Technology	41(38)	High	Mississippi State University
76	1/1/2015	Ohio State University	41(86)	High	The University of Alabama
77	1/1/2015	University of Wisconsin	32(50)	High	Auburn University
78	1/2/2015	University of Houston	144(115)	Middle	University of Pittsburgh
79	1/2/2015	Oklahoma State University	196(171)	Low	University of Washington
80	1/12/2015	Ohio State University	41(86)	High	University of Oregon

Table A1. Cinderella Event and the Treated and Control Universities

Nr.	Event Date	Treated School	US News(Forbes)	Group	Control School
81	12/22/2015	University of Akron Main Campus	377(.)	Low	Utah State University
82	12/23/2015	Georgia Southern University	342(463)	Low	Bowling Green State University
83	12/26/2015	University of Nebraska	152(191)	Middle	University of California
84	12/29/2015	University of Nevada	204(167)	Low	Colorado State University
85	12/31/2015	Clemson University	80(98)	High	University of Oklahoma
86	12/31/2015	University of Houston	144(115)	Middle	Florida State University
87	1/2/2016	Texas Christian University	105(220)	Middle	University of Oregon
88	12/17/2016	San Diego State University	109(77)	Middle	University of Houston
89	12/22/2016	University of Idaho	179(281)	Middle	Colorado State University
90	12/24/2016	University of Hawaii at Manoa	171(172)	Middle	Middle Tennessee State University
91	12/27/2016	Wake Forest University	26(88)	High	Temple University
92	12/27/2016	University of Minnesota	54(75)	High	Washington State University
93	12/27/2016	Baylor University	91(152)	Middle	Boise State University
94	12/28/2016	Northwestern University	12(11)	High	University of Pittsburgh
95	12/28/2016	Kansas State University	165(183)	Middle	Texas A & M University
96	12/30/2016	Florida State University	54(65)	High	University of Michigan
97	1/2/2017	Clemson University	80(98)	High	The University of Alabama
98	12/16/2017	Boise State University	296(353)	Low	University of Oregon
99	12/16/2017	Georgia State University	196(365)	Low	Western Kentucky University
100	12/20/2017	Louisiana Tech University	296(457)	Low	Southern Methodist University
101	12/23/2017	Appalachian State University	.(256)	Low	University of Toledo
102	12/29/2017	New Mexico State University	244(418)	Low	Utah State University
103	12/30/2017	Mississippi State University	214(250)	Low	University of Louisville
104	1/1/2018	University of Central Florida	121(110)	Middle	Auburn University
105	1/1/2018	University of South Carolina	121(163)	Middle	University of Michigan
106	12/21/2018	Florida International University	98(138)	Middle	University of Toledo
107	12/26/2018	University of Minnesota	54(75)	High	Georgia Institute of Technology
108	12/27/2018	Baylor University	91(152)	Middle	Vanderbilt University
109	12/29/2018	University of Florida	30(26)	High	University of Michigan
110	12/31/2018	Northwestern University	12(11)	High	University of Utah
111	12/31/2018	Oklahoma State University	196(171)	Low	University of Missouri
112	1/1/2019	The University of Texas at Austin	48(46)	High	University of Georgia
113	1/1/2019	University of Kentucky	152(160)	Middle	Penn State University
114	1/1/2019	University of Iowa	98(155)	Middle	Mississippi State University
115	1/7/2019	Clemson University	80(98)	High	The University of Alabama
116	12/20/2019	Kent State University at Kent	231(.)	Low	Utah State University
117	12/21/2019	Liberty University	392(.)	Low	Georgia Southern University
118	12/21/2019	Florida Atlantic University	189(188)	Low	Southern Methodist University
119	12/26/2019	Louisiana Tech University	296(457)	Low	University of Miami
120	12/30/2019	University of Louisville	179(252)	Middle	Mississippi State University
121	12/31/2019	The University of Texas at Austin	48(46)	High	University of Utah
122	1/1/2020	University of Minnesota	54(75)	High	Auburn University

Table A2. The bowl game effect on short-term labor market outcomes in "high-six" seasons

This table reports the estimates of β coefficients from OLS regression: $Log(Avg.\ Salary\ (Year\ 0\ to\ Year\ 3)^{u}_{i,c}) = \sum_{c=1}^{6} \beta_c \boldsymbol{Cohort_c} \times Treated_i + \sum_{c=1}^{6} \delta_c Cohort_c + \gamma_i Treated_i + Fixed\ effects + \epsilon^{u}_{i,c}$, where i indexes universities, c cohorts, and u individuals. The sample includes schools that win five regular-season games and do not appear in bowl games, and those that win six regular-season games in "high-six" seasons. $Treated_i$ is an indicator equal to one for schools that win six regular-season games in "high-six" seasons. $Cohort_c$ includes indicators for six student cohorts: alumni cohorts who graduate before the event and the most recent graduates; incumbent students (freshman, sophomore, junior, and senior cohorts during the Cinderella event); and the Cinderella cohort who enroll in the next academic year following the event. The earnings for students who graduate before the Cinderella events serve as the baseline. Columns (1) and Column (2), Column (3) and Column (4), and Column (5) and Column (6) report the effects of athletic success for low-ranked, middle-ranked, and high-ranked schools, respectively. The standard errors are two-way clustered at the school and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Low	Low	Middle	Middle	High	High
Dept. Variable:	Log(Avg. Salary (Year 0 to 3))					
Graduates and Alumni×Treated	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Senior×Treated	-0.015**	-0.011	-0.003	0.003	0.011*	0.007
	(0.006)	(0.007)	(0.007)	(0.005)	(0.006)	(0.006)
Junior×Treated	-0.020**	-0.018*	-0.010*	-0.006	0.017**	0.014**
	(0.009)	(0.010)	(0.005)	(0.004)	(0.006)	(0.005)
Sophomore×Treated	-0.034**	-0.031**	-0.018*	-0.015*	0.019**	0.011
	(0.014)	(0.014)	(0.009)	(0.007)	(0.008)	(0.007)
Freshman×Treated	-0.039***	-0.042***	-0.020**	-0.016**	0.022**	0.010
	(0.013)	(0.012)	(0.010)	(0.007)	(0.009)	(0.006)
Cinderella×Treated	-0.045**	-0.043***	-0.017	-0.009	0.029**	0.015**
	(0.017)	(0.015)	(0.014)	(0.009)	(0.011)	(0.007)
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Game Year×Year FE	Yes	No	Yes	No	Yes	No
Game Year×Year×Major FE	No	Yes	No	Yes	No	Yes
Observations	2,316,587	1,083,315	2,680,760	1,249,222	2,785,966	1,328,550
R-squared	0.072	0.147	0.062	0.137	0.072	0.147

Table A3. The Cinderella effect on universities' applications

This table reports the estimates of β coefficients from the following specification: $Y_{i,t} = \beta_s Treated_i \times Post_t + \delta_t Post_t + \gamma_i Treated_i + Fixed\,effects + \epsilon_{i,t}$, where i indexes universities and t indexes years. $Y_{i,t}$ is one of the following: number of applications, acceptance rate, admission yield, 25th percentile SAT score, and 75th percentile SAT score. The model uses data for the three years preceding the event, the event year, and four subsequent years. The variable $Treated_i$ is an indicator equal to one for schools that unexpectedly win a bowl game. $Post_t$ is an indicator for the post-event period. The standard errors are two-way clustered at the school and year levels. Panel A3.A reports results for middle-ranked schools, and Panel A3.B reports results for high-ranked schools. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A3.A: Middle-ranked schools

	(1)	(2)	(3)	(4)	(5)
Dept. Variable:	Log(Applications)	Acceptance Rate (%)	Admission Yield (%)	SAT25th	SAT75th
Treated×Post	0.019	-0.243	-0.290	0.004	-1.068
	(0.020)	(1.006)	(0.663)	(3.742)	(3.747)
University FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,173	1,173	1,173	1,096	1,096
R-squared	0.957	0.890	0.841	0.970	0.963

Panel A3.B: High-ranked schools

	(1)	(2)	(3)	(4)	(5)
Dept. Variable:	Log(Applications)	Acceptance Rate (%)	Admission Yield (%)	SAT25th	SAT75th
Treated×Post	0.055	-3.236**	1.528**	-2.232	-1.428
	(0.032)	(1.352)	(0.621)	(3.072)	(3.786)
University FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,116	1,116	1,116	1,057	1,057
R-squared	0.956	0.913	0.853	0.971	0.966

Table A4. The Cinderella effect on universities' financials

This table reports the estimates of β coefficients from Poisson pseudo-maximum likelihood regression: $Y_{i,t} = \beta_s Treated_i \times Post_t + \delta_t Post_t + \gamma_i Treated_i + Fixed\ effects + \epsilon_{i,t}$, where $Y_{i,t}$ denotes the revenue or expenditure of university i in year t. The model uses data for the three years preceding the event, the event year, and four subsequent years. The variable $Treated_i$ is an indicator equal to one for schools that unexpectedly win a bowl game. $Post_t$ is an indicator for the post-event period. The standard errors are two-way clustered at the school and year levels. Panel A4.A (Panel A4.B) reports results on revenue (expenditure) for middle-ranked schools, and Panel A4.C (Panel A4.D) reports the corresponding results for high-ranked schools. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A4.A: Revenue (Middle-ranked schools)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Middle					
Dept. Variable:	Tuition	Federal	State	Local and Private	Auxiliary	Total Revenue
Post×Treated	-0.022	-0.000	0.039*	-0.024	0.027	0.026*
	(0.018)	(0.022)	(0.021)	(0.023)	(0.023)	(0.016)
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,216	1,216	1,216	1,216	1,216	1,216
Pseudo R-squared	0.982	0.986	0.978	0.972	0.959	0.988

Panel A4.B: Expenditure (Middle-ranked schools)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	Middle							
Dept. Variable:	Instruction	Research	Academic	Public Service	Institute Support	Scholarship	Auxiliary	Total Expense
Post×Treated	-0.002	-0.017	0.019	-0.027	0.001	-0.029	-0.017	0.018
	(0.013)	(0.023)	(0.025)	(0.062)	(0.033)	(0.044)	(0.021)	(0.014)
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,216	1,216	1,216	1,192	1,216	1,117	1,216	1,216
Pseudo R-squared	0.988	0.989	0.976	0.963	0.956	0.903	0.970	0.994

Table A4: The Cinderella effect on universities' financials

Panel A4.C: Revenue (High-ranked schools)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	High					
Dept. Variable:	Tuition	Federal	State	Local and Private	Auxiliary	Total Revenue
Post×Treated	-0.011	-0.008	0.014	-0.042	0.041*	0.021**
	(0.019)	(0.008)	(0.023)	(0.028)	(0.022)	(0.010)
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,163	1,163	1,163	1,163	1,163	1,163
Pseudo R-squared	0.982	0.985	0.983	0.974	0.946	0.979

Panel A4.D: Expenditure (High-ranked schools)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	High							
Dept. Variable:	Instruction	Research	Academic	Public Service	Institute Support	Scholarship	Auxiliary	Total Expense
Post×Treated	-0.009	-0.005	0.005	-0.026	-0.021	0.073**	0.012	0.022*
	(0.014)	(0.015)	(0.031)	(0.041)	(0.031)	(0.034)	(0.025)	(0.012)
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,163	1,163	1,163	1,127	1,163	1,067	1,163	1,163
Pseudo R-squared	0.982	0.989	0.977	0.956	0.959	0.933	0.962	0.985

Appendix B The Cinderella Effects on Perferences toward Sports

In this appendix, we provide suggestive evidence that athletic success can shift individuals' preferences from academic activities toward sports-related activities, supporting the theoretical framework of Akerlof and Kranton (2000) and Brock and Durlauf (2001). We do so by examining how households allocate time between the two. We employ data from the American Time Use Survey (ATUS) in the Integrated Public Use Microdata Series (IPUMS) database. The ATUS provides detailed information on individuals' time use across a comprehensive set of daily activities from 2003 to 2024. We focus on household time spent on two categories of activities: sports versus homework.

A limitation of the ATUS data is that it does not report individuals' college affiliations or years of education. As a result, we cannot directly identify students enrolled at the winning or losing schools in a Cinderella event. Instead, we compare household time use in counties where winning universities are located (treated counties) to that in counties where losing universities are located (control counties) before and after the Cinderella event. To approximate the behavior of the student population within a county, we focus on individuals aged 15 to 24, who most closely represent high school and current college students.[15] We later use individuals aged 25 and older as a placebo group. Because of this data limitation, our findings should be interpreted as intent-to-treat effects. In addition to time allocation, we also collect data on individual demographics, such as gender, for all individuals aged 15 to 85.

Table B1 reports summary statistics of time allocation for 2,344 individuals aged 15 to 24. Panel B1.A shows that on average, individuals spend 42 minutes per day on homework and 34 minutes per day on sports, with standard deviations of 91 and 72 minutes, respectively. The majority of individuals report no daily engagement in either activity. To capture relative preferences for sports versus academic activities, we construct the variable *Diff(Sport-HWork)*, defined as time spent on sports minus time spent on homework. The mean of this measure is -8 minutes, indicating that individuals spend 8 more minutes per day on homework on average. Panel B1.B compares time

[15] See College Enrollment and Student Demographic Statistics.

allocation by gender. There is no significant difference in homework time between females and males, though, not surprisingly, males spend more time on sports – about 26 minutes more per day. We explore gender heterogeneity in the effects of athletic success in subsequent analyses.

To examine whether athletic success affects household time allocation, we use the following specification:

$$Y_{i(c),t} = \beta_s Treated_{i(c)} \times Post_t + \delta_t Post_t + \gamma_c Treated_{i(c)} + Fixed\,effects + \varepsilon_{i(c),t}. \quad (5)$$

where i indexes individuals residing in county c, and t indexes calendar years. The outcome variable $Y_{i(c),t}$ is either the time allocated to sports (*Sport*) or the difference between the time spent on sports and the time spent on homework (*Diff(Sport-HWork)*). The indicator $Treated_{i(c)}$ equals one if individual i resides in the treated county where a winning university is located in a Cinderella event. We include county fixed effects to control for time-invariant differences across counties and game pair by year fixed effects to absorb common factors at the game level. Standard errors are two-way clustered at the county and year levels.

Table B2 reports the results. Columns (1) and (2) use *Sport* as the dependent variable. Column (1) shows that individuals increase daily time spent on sports by 52 minutes, on average, following athletic success. Because the distribution of time spent on sports is highly skewed with a mass of zeros, column (2) estimates a Poisson pseudo maximum likelihood (PPML) specification. The estimates suggest that time spent on sports increases by 341.5 percent ($e^{1.485} - 1$).

We verify the parallel trend assumption by estimating dynamic treatment effects over a five-year window before and after the Cinderella event:

$$Y_{i(c),t} = \sum_{s=-5}^{5} \beta_s Treated_{i(c)} \times I_s + \sum_{s=-5}^{5} \delta_s I_s + \gamma_c Treated_{i(c)} + Fixed\,effects + \varepsilon_{i(c),t}. \quad (6)$$

where I_s denotes event time indicators, and the remaining variables are defined as in Equation (5). The year before the Cinderella event serves as the reference group and is omitted from the estimation.

Figure B1 presents the results. Panel B1.A reports estimates from the OLS specification, while Panel B1.B reports estimates from the PPML specification. We find no statistically significant differences in sports time allocation between households in treated and control counties during the five years prior to the Cinderella event, supporting the parallel trends assumption. In contrast, following the event, households in treated counties spend more time on sports relative to households in control counties.

To better capture the relative preferences of the two activities, column (3) of Table B2 uses *Diff(Sport-HWork)* as the dependent variable. It shows that following the Cinderella events, individuals spend an additional 53 minutes per day on sports relative to homework. Columns (4) and (5) show that this effect is driven by males, while the estimates for females are not statistically significant.

One potential concern is that collegiate athletic success may affect household behavior through broader shifts in local culture rather than through the university environment or student behavior. Prior work documents that emotional responses to sports outcomes can influence local household behavior beyond the education context (Card and Dahl, 2011). To address this concern, we perform a placebo test focusing on households aged 25 and above – who are less likely to be engaged in higher education. Table B3 shows no significant changes in sports participation this group. Taken together, the results in this appendix provide suggestive evidence that collegiate athletic success plays a role in households' time allocation and may contribute to a shift in preferences from academic activities to sport-related leisure.

Figure B1. The Cinderella effect on time allocation for households aged 15 to 24

This figure plots the estimates of β coefficients from the OLS specification in Panel A and from the Poisson pseudo maximum likelihood specification in Panel B: $Y_{i(c),t} = \sum_{s=-5}^{5} \beta_s Treated_{i(c)} \times I_s + \sum_{s=-5}^{5} \delta_s I_s + \gamma_c Treated_{i(c)} + Fixed\ effects + \varepsilon_{i(c),t}$, where i indexes individuals residing in county c and t indexes calendar years. The sample includes households in counties where winning schools are located and in counties where losing schools are located. $Treated_{i(c)}$ equals one if individual i resides in the county where a winning school is located. I_s denotes event time indicators. Time spent on sports one year before the Cinderella event serves as the baseline. Standard errors are two-way clustered at the county and year levels. The bars surrounding each coefficient represent the 5% and 95% confidence intervals.

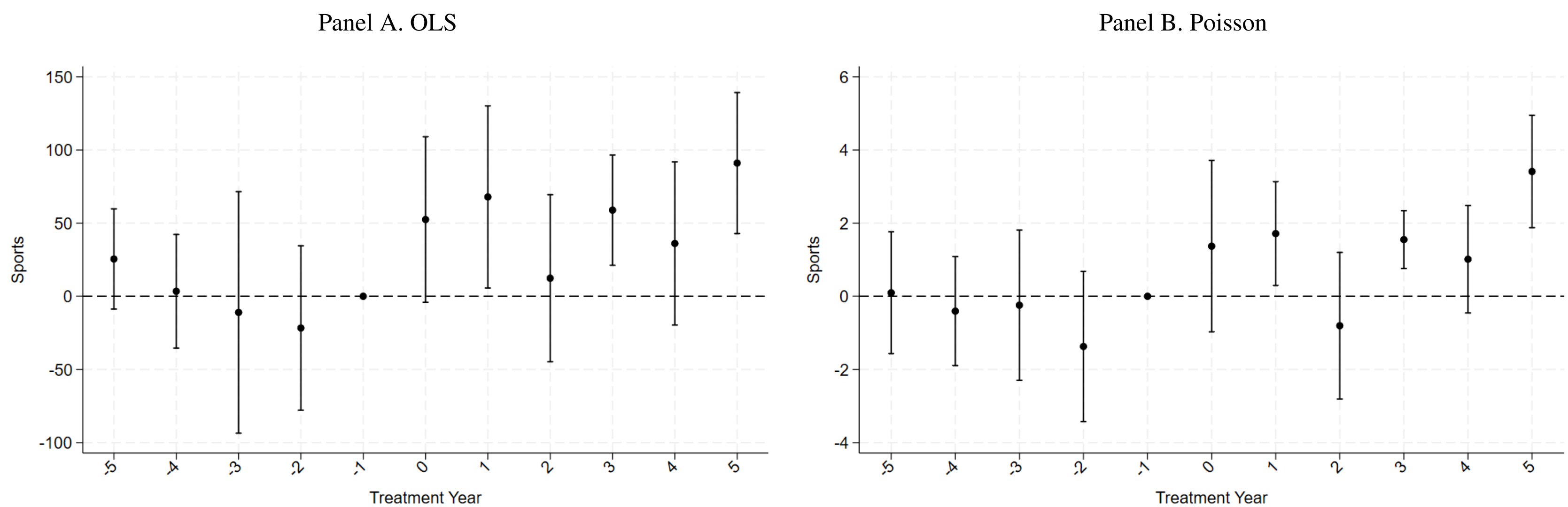


Table B1. Summary statistics of time allocations

This table provides variable definitions and summary statistics of time allocation variables. *HWork* indicates the minutes per day each respondent reported spending on homework. *Sport* indicates the minutes per day each respondent reported spending on sports, exercise, and recreational activities. *Diff(Sport-HWork)* indicates the difference in time spent on sports and homework. Panel B1.A reports the summary statistics for the overall sample. Panel B1.B separately reports time allocation for females and males. The last column of Panel B1.B reports differences in means between the two subsamples.

Panel B1.A. Overall sample

Variable	Obs	Mean	Std. dev.	P25	P50	P75
HWork	4,665	41.89	91.17	0	0	30
Sport	4,665	33.64	72.15	0	0	25
Diff(Sport-HWork)	4,665	-8.32	118.53	0	0	0

Panel B1.B. Subsample based on gender

	Female		Male		
	N	Mean	N	Mean	Diff in Mean
HWork	2,355	43.66	2,310	40.09	-3.57
					(2.67)
Sport	2,355	20.97	2,310	46.56	25.59***
					(1.06)
Diff(Sport-HWork)	2,355	-22.67	2,310	6.31	28.98***
					(1.74)

Table B2. The Cinderella effect on time allocation for households aged 15 to 24

This table reports the estimates of β coefficients from the following specification: $Y_{i(c),t} = \beta_s Treated_{i(c)} \times Post_t + \delta_t Post_t + \gamma_c Treated_{i(c)} + Fixed\ effects + \varepsilon_{i(c),t}$, where i indexes individuals residing in county c, and t indexes calendar years. The outcome variable $Y_{i(c),t}$ is either the time allocated to sports or the difference between the time spent on sports and the time spent on homework. The indicator $Treated_{i(c)}$ equals one if individual i resides in the county containing a Cinderella school. $Post_t$ is an indicator for the post-event period. The standard errors are two-way clustered at the school and year levels. The sample includes households aged 15 to 24 in counties where winning or losing schools are located. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Sample:	All	All	All	Female	Male
Dept. Variable:	Sports (OLS)	Sports (Poisson)	Diff(Sports-HWork) (OLS)	Diff(Sports-HWork) (OLS)	Diff(Sports-HWork) (OLS)
Post×Treated	52.179***	1.485***	52.880**	-1.993	129.707**
	(12.800)	(0.379)	(24.373)	(47.274)	(18.271)
County FE	Yes	Yes	Yes	Yes	Yes
Year×Game Pair	Yes	Yes	Yes	Yes	Yes
Observations	4523	4093	4523	2132	2172
R-squared	0.115	0.116	0.129	0.188	0.216

Table B3. The Cinderella effect on time allocation for households aged 25 to 85

This table reports the estimates of β coefficients from the following specification: $Y_{i(c),t} = \beta_s Treated_{i(c)} \times Post_t + \delta_t Post_t + \gamma_c Treated_{i(c)} + Fixed\ effects + \varepsilon_{i(c),t}$, where i indexes individuals residing in county c, and t indexes calendar years. The outcome variable $Y_{i(c),t}$ is either the time allocated to sports or the difference between the time spent on sports and the time spent on homework. The indicator $Treated_{i(c)}$ equals one if individual i resides in the county containing a Cinderella school. $Post_t$ is an indicator for the post-event period. The standard errors are two-way clustered at the school and year levels. The sample includes households aged 25 to 85 in counties where winning or losing schools are located. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Sample:	All	All	All
Dept. Variable:	Sports (OLS)	Sports (Poisson)	Diff(Sports-HWork) (OLS)
Post×Treated	0.177	0.047	0.165
	(1.165)	(0.103)	(1.157)
County FE	Yes	Yes	Yes
Year×Game Pair	Yes	Yes	Yes
Observations	36,270	35,801	36,270
R-squared	0.025	0.039	0.026