Leveling the Playing Field or Tipping the Scales? NIL, Transfers, and Competitive Balance*

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Abstract

Recent rule changes have dramatically reduced restrictions on mobility and compensation for student-athletes. These changes should increase the ability of student-athletes to enroll in schools where they are most valued. However, the implications for competitive balance are ambiguous. We evaluate the impact of the recent rule changes on competitive balance in college football and men's college basketball. We find that a particular form of competitive balance has increased in both sports: individual team success and conference standings order both have become less persistent from one season to the next. This increase is strongest in the so-called "power" conferences, particularly for football, suggesting that the rule changes have leveled the playing field by helping weaker teams lure talent away from top teams. Many of our findings are stronger for college football than men's college basketball.

keywords: competitive balance; NCAA; name, image, and likeness (NIL); transfer portal; college football; college basketball

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1 Introduction

College athletics generates tens of billions of dollars in revenue annually (Knight Commission on Intercollegiate Athletics, 2024). College athletics also contributes many of the most viewed live television broadcasts every year (Karp, 2025). These facts make college athletics highly impactful on college campuses and on society as a whole. For example, athletics coaches are frequently the highest paid state employees (Gibson, 2019), while prior research has shown that athletic success increases applications, enrollment, incoming SAT scores, academic reputation, donations, and research productivity (Anderson, 2017; Meer and Rosen, 2009; Tabakovic and Wollmann, 2019). College athletics is currently undergoing a major transformation related to player compensation and player movement across teams that has the potential to impact both the financial and competitive landscape. Given prior work showing the benefits of athletics success, this transformation has important implications for competitive balance and priorities for schools.

Historically, student-athlete mobility and compensation was highly restricted compared to other students on campus or other athletes in professional sports leagues. Mobility was restricted by rules limiting the ability of student-athletes to transfer and compete immediately at another institution. Most transfers were required to sit out one year before competing, with limited waiver mechanisms, and some athletic conferences imposed additional restrictions on intra-conference transfers.[1] Compensation was restricted by NCAA rules that prohibited athletes from receiving compensation beyond scholarships and limited stipends covering education-related expenses.[2]

Many of these restrictions were removed in 2021, allowing student-athletes to be com-

[1]Athletic conferences historically reflected regional groupings, although recent realignment has reduced the importance of geography. Conference prestige varies substantially, so restrictions on intra-conference transfers could force athletes to trade off geographic proximity to home and conference quality.

[2]Professional leagues also have restrictions on movement and compensation, but in very different forms. Most professional leagues restrict the ability of players to choose their first team via drafts and rookie contracts with pre-determined values, but provide greater post-entry mobility through free agency and negotiated contracts. Compensation is constrained through mechanisms such as salary caps, luxury taxes, and collective bargaining agreements.

pensated in a way that more closely aligns with their market value and to move more freely between schools. In April of 2021, due to ongoing legal pressure, the National Collegiate Athletic Association (NCAA) changed its rules to allow all athletes a one-time transfer during their college career without the requirement to sit out for a year.[3] Additionally, four of the five "power" conferences that had rules in place restricting intra-conference transfers changed their rules in 2021 to remove the restrictions.[4] In June 2021, the Supreme Court ruled that the NCAA could not legally limit education-related payments to students in NCAA v. Alston. The NCAA subsequently changed its rules to allow athletes to legally profit from their 'Name, Image and Likeness' (NIL) and earn additional income while remaining eligible to participate.

Initial public perception was that these changes would further tip the scales in favor of schools with a history of success, as such schools were perceived to have greater access to financial resources and marketing opportunities that could be used to compensate players and lure them from other schools. Public perception has since shifted, and NIL plus the transfer era are generally seen as having leveled the playing field to some degree. Consider, for example, the following two quotes from Nick Saban (former college football coach, current sportscaster, and record holder for most college football national championships):

> You have a pay-for-play system and a free agency system that has no guidelines so there's no competitive balance... You're going to create a caste system where the rich will get richer and the poor will get poorer. (Nick Saban, March 12, 2024)

> I do think that the culture in college football right now, with name, image and likeness and paying players money, has actually maybe hurt the SEC a little bit... Kids are not growing up wanting to go to Alabama, wanting to go to Georgia, wanting to go to Florida, wanting to go to Texas. They want to go wherever, to who is going to pay them the most money. (Nick Saban, October 11, 2025)

The theory is also ambiguous. On one hand, removing restrictions on player mobility and compensation should allow for a more efficient distribution of talent, which should improve

[3]The NCAA later changed its rule again in 2024, due to continued legal pressure, to remove limits on the number of times an athlete can transfer during their college career.

[4]The ACC, Big 12, PAC 12, and SEC all had restrictions on intra-conference transfers, while the Big Ten removed their restrictions in 2011.

some dimensions of competitive balance. Greater transfer mobility should help alleviate poor matches between schools and student-athletes, while greater ability to compensate student-athletes should provide schools with weaker reputations a new avenue for acquiring talented players.[5] This re-allocation of talent should increase year-to-year volatility in team performance and conference standings due to increased roster turnover. It could also reduce large talent gaps between teams in a given year, regardless of standings order. On the other hand, these impacts could be dampened if the previous transfer rule allowed enough movement to alleviate many mismatches or if there is a strong correlation between other relatively fixed attributes that may attract student-athletes and the ability to monetize NIL.[6] Furthermore, through the lens of a "winner-take-all" market or "superstar" market, if the prestigious programs are able to more effectively monetize student-athletes then NIL and the transfer era could amplify existing power dynamics, resulting in greater concentration of talent among top schools.[7]

There is little empirical evidence available so far to augment the theory. Current evidence suggests that NIL has impacted which schools student-athletes choose to attend, but with mixed implications for competitive balance (Badger, Chyz and Gaertner, 2025; Goldman and Jacob, 2025; Li and Derdenger, 2025; Owens, Rennhoff and Roach, 2025; Pitts and Evans, 2025). We fill in this gap using 15 years of data on team performance. We evaluate competitive balance in two primary forms. We evaluate year-to-year dynamics based on the persistence between lagged versus current performance and based on the average change in standings rank from one season to the next. We also evaluate within-season equality. Reduced persistence would imply increased ex ante uncertainty over future standings, but does not necessarily imply greater within-season competitive equality. We therefore also

[5]Without compensation-based competition for players, student-athletes may sort into schools based on relatively fixed attributes (e.g., past success, facilities, alumni and network effects, media exposure, and coaches), making it difficult for teams with weaker reputations to compete.

[6]Prior to the NIL era, a primary way schools competed for student-athletes was by spending money on amenities such as player facilities.

[7]For example, a top program might accumulate an even greater surplus of talent if they can more easily convince student-athletes to forego immediate playing time at other schools in exchange for greater compensation.

evaluate within-season equality based on the standard deviation of winning percentage across teams in a conference in a given season. We analyze college football and college basketball separately using regression models that account for conference affiliation and conference realignment.

We find that persistence of team performance across years reduced beginning in 2021 when NIL and the transfer era were introduced.[8] This result holds across sports, but is more pronounced for college football. We also find that the reduction in persistence is primarily driven by teams in the "power" conferences. Consistent with a reduction in persistence of team performance across seasons, we also find an increase in the average absolute change of teams' conference standings rank across seasons beginning in 2021. This result is also more pronounced for football than basketball and is primarily driven by the power conferences. There is little evidence of a change in the standard deviation of performance across teams in a conference in a given year, with the exception of non-power football conferences.

These results suggest that NIL and the transfer era have so far led to an increase in competitive balance in college sports. This increase has taken the form of increased year-to-year dynamics, with more year-to-year variability in team performance and conference standings order. There is less evidence of increased equality across teams in a given year. That is, NIL and increased transfers appear to have leveled the playing field to some degree, likely by allowing weaker teams to lure surplus talent away from more powerful teams. Importantly, these increases in year-to-year variability in team performance and standings order are primarily existent in the power conferences. This suggests that teams with greater reputations were likely benefiting from market power advantages (i.e., brand capital) that allowed them to accumulate and retain significant talent surpluses relative even to their competitors in the same conference.[9] However, there are two important confounders for our

[8]Our analysis uses the 2021-2022 academic year as the treatment year. We also performed robustness checks using the 2022-2023 academic year as the treatment year, due to the possibility that it took time for institutions to adjust to the new rules. The results are similar to those reported in the paper and are available upon request.

[9]Houston, Groothuis and Guignet (2025) showed that football programs in the Southeastern Conference (SEC) have systematic recruiting advantages even after controlling for program success, highlighting how

results: conference realignment and the extra year of eligibility granted to all athletes who were eligible during the 2020-2021 seasons that were impacted by COVID-19. We present some robustness checks in which we only analyze teams that did not switch conferences during the treatment period. The robustness results for team performance persistence are similar to the main results for both sports, while the standings rank mobility results are no longer significant for men's basketball. The COVID-19 eligibility impact is harder to disentangle and will likely require more years of data.

Many of the results suggest somewhat larger impacts for college football than college basketball. There are a few important differences between the two sports that could explain the different results, although we are not able to cleanly distinguish between them. First, basketball is often considered a "superstar" sport since the small number of players on the court allows an individual star to have a greater impact on team performance. This means that high-end talent may matter more than depth, in which case any impact of NIL and the transfer era on reducing talent surpluses and shortages may be less consequential if it primarily impacts the ability of teams to retain talent depth. Second, to the extent that talent depth also matters, basketball teams may be better able to utilize surplus talent than football teams. For example, a football team can only play one quarterback, while a basketball team can play multiple point guards at once. This means any impact of NIL and the transfer era on reducing talent surpluses may be dampened in basketball. Finally, college basketball has more outside options than college football.[10] This means that talent surpluses and shortages may tend to resolve themselves relatively quickly in basketball even without NIL and the transfer era.

Our results provide evidence not just on the competitive landscape of college sports, but also on the understanding of labor markets broadly. Our results show that allowing

conference structure drives persistent talent imbalances. Our results suggest that these imbalances exist even across teams within the power conferences.

[10]College basketball players can leave for the National Basketball Association after one year, whereas college football players cannot leave for the National Football League until they have played three years of college football. The NBA also has a developmental league, unlike the NFL. Finally, there are also many international professional basketball leagues, whereas football has very few.

labor to move more freely and efficiently across organizations can affect competition, volatility, and relative standing of organization performance. This result can benefit industries and consumers alike: maintaining outcome uncertainty in sports maximizes fan interest and revenue (El-Hodiri and Quirk, 1971; Humphreys and Miceli, 2020; Rottenberg, 1956; Szymanski, 2003), while competition among firms generates "creative destruction" and enhances productivity (Aghion and Howitt, 1992; Davis, Haltiwanger and Schuh, 1998; Foster and Haltiwanger, 2001; Olley and Pakes, 1996). Furthermore, our results are related to prior work on non-compete agreements and occupational licensing. In those literatures, worker mobility is reduced which in turn reduces competition, dynamism, and innovation (Government Accountability Office, 2023; He, 2025; Johnson, Lavetti and Lipsitz, 2025; Kleiner and Xu, 2025; Kleiner and Wang, 2025; Lipsitz and Starr, 2022; Marx and Fleming, 2012; Reinmuth and Rockall, 2023), whereas our results suggest that reduced student-athlete mobility leads to talent hoarding and persistent dominance.

Section 2 briefly discusses how our work relates to existing research. Section 3 describes our data and empirical methodology. Section 4 presents and discusses our results. Section 5 concludes.

2 Related Literature

Most of the research on the economics of NIL and the transfer era of college sports so far has focused on the distribution of talent across teams based on publicly-available recruiting data. This research has consistently found that NIL has impacted the distribution of talent, with evidence that higher-ranked athletes are more likely to attend universities with greater ability to monetize NIL, lower-ranked football programs, less-selective admissions and lower mid-career income, and lower in-state income taxes (Badger, Chyz and Gaertner, 2025; Goldman and Jacob, 2025; Li and Derdenger, 2025; Owens, Rennhoff and Roach, 2025; Pitts and Evans, 2025).

Current research is mixed about the implications for competitive balance. Owens, Rennhoff and Roach (2025) and Pitts and Evans (2025) suggest that the changes in recruiting they find are unlikely to level the playing field competitively. Goldman and Jacob (2025) and Li and Derdenger (2025), on the other hand, find evidence of reduced point spreads from sports books and more wins for teams in low income tax states, respectively. Our paper differs from prior work in that we consider more dimensions of competitive balance, we analyze men's college basketball in addition to college football, and we focus on market power as an important moderator.

Our findings are also related to prior work on the economic impacts of non-compete agreements and occupational licensing, which restrict worker mobility and freedom. Non-compete agreements restrict the ability of employees to work for (or start) competitors. Occupational licensing involves government-mandated permits to legally work in a given profession, which restricts the ability of workers to freely enter professions or switch between firms.[11] Prior work has shown that non-compete agreements and occupational licensing reduce worker mobility, competition, dynamism, and innovation (Government Accountability Office, 2023; He, 2025; Johnson, Lavetti and Lipsitz, 2025; Kleiner and Xu, 2025; Kleiner and Wang, 2025; Lipsitz and Starr, 2022; Marx and Fleming, 2012; Reinmuth and Rockall, 2023). Lessons learned from this literature broadly suggest that removing restrictions on student-athlete mobility is likely to have some beneficial impacts on competitive outcomes.

3 Data

We obtain all our data from Sports Reference LLC (sports-reference.com), specifically from the College Football Reference and College Basketball Reference websites. Sports Reference aggregates official NCAA statistics and provides comprehensive historical data for all Division I teams, including win-loss records, conference affiliations, and strength metrics.

[11] E.g., occupational licenses are often state-specific, which impacts the ability of employees to easily switch to a firm in a different state.

Our dataset spans the 2010 through 2024 seasons for both sports, providing 15 years of observations that capture the period before and after the implementation of NIL and transfer era policies in 2021. We developed Python scripts to systematically scrape team performance data from sports-reference.com for all seasons from 2010 through 2024. The scraping process collects all Division I teams for each season and standardizes column names to ensure consistency across seasons. The final football dataset contains 1,921 team-year observations across 167 conference-year units, while the basketball dataset contains 5,291 team-year observations across 482 conference-year units.[12]

For each team-year observation, we collect the following variables: team name and conference affiliation; overall win-loss record and winning percentage; conference win-loss record and winning percentage; Simple Rating System (SRS) score; and average margin of victory (MOV). The Simple Rating System is a team strength metric that accounts for both margin of victory and strength of schedule, with zero representing an average team. A team with an SRS of +10 would be expected to beat an average team by 10 points on a neutral field. Average margin of victory is the average point total difference across all games.

Conference membership and naming conventions changed during our sample period, with teams moving between conferences for strategic and financial reasons. These moves complicate the calculation of competitive balance within a conference-year and persistence in team performance year-over-year, as a conference's standard deviation of winning percentages or a team's change in win percentage could reflect the quality of new opponents in the conference. We use conference fixed effects combined with a count of the number of teams in each conference-year to adjust for conference realignment in our main results. We also exclude teams who switch conferences as a robustness check. To maintain consistency in our conference fixed effects, we recode all conference names to be consistent over time. Most notably, the Pacific-10 Conference expanded to become the Pacific-12 Conference starting in the 2011 season. We recode all "Pac-10" labels (appearing in 2010 data) as "Pac-12" throughout the

[12]The difference in conference-year observations reflects the greater number of Division I basketball teams and conferences compared to football.

dataset. This ensures that conference fixed effects capture the same underlying conference entity across all years rather than treating the Pac-10 and Pac-12 as separate conferences.[13] Ensuring consistent conference names over time is also necessary for the analysis where we evaluate heterogeneous effects in the historical "power" conferences.

Our analysis uses two complementary levels of aggregation: conference-year observations and team-year observations. Each level examines different aspects of competitive balance and uses a distinct set of dependent and independent variables. Table 1 summarizes the sample size of the scraped data for both levels of aggregation.

The team-year sample retains individual team-year observations to examine team-level performance persistence and volatility. Our team-year dependent variables include:

1. **Win Percentage**: Used as a dependent variable in persistence models to test whether past performance predicts current performance.

2. **Conference Win Percentage**: Used as a dependent variable in persistence models to test whether past within-conference performance predicts current within-conference performance.

3. **Simple Rating System (SRS)**: Used as a dependent variable in alternative persistence models focusing on a continuous measure of team strength rather than win-loss records.

4. **Margin of Victory (MOV)**: Used as a dependent variable in alternative persistence models focusing on a continuous measure of game outcomes rather than binary win-loss records.

The team-year sample of analysis contains 1,782 team-year observations for football (down from 1,921 total observations due to excluding 139 observations from 2010 that lack

[13] We ignore division identifiers (e.g., "SEC (West)") for conference labels, retaining only the parent conference name. Division-level designations are not consistently present across all conferences and years, so our analysis focuses on conference-level competitive balance.

lagged values for the team performance persistence models) and 4,923 team-year observations for men's basketball (down from 5,291 total observations due to excluding 368 observations from 2010 without lagged values).

The conference-year sample aggregates team-level data to examine competitive balance within conferences over time. For each conference-year unit, we construct six measures of within-conference competitive balance:

1. **Standard Deviation of Win Percentage**: The standard deviation of overall winning percentage across all teams in a conference-year. Larger values indicate larger dispersion in team success, suggesting less competitive balance.

2. **Standard Deviation of Conference Win Percentage**: The standard deviation of winning percentage in conference games across all teams in a conference-year. Larger values indicate larger dispersion in team success, suggesting less competitive balance.

3. **Standard Deviation of SRS**: The standard deviation of Simple Rating System scores across teams in a conference-year. This provides an alternative measure of competitive dispersion based on team strength rather than win-loss records.

4. **Standard Deviation of MOV**: The standard deviation of overall average Margin of Victory across teams in a conference-year. This provides another alternative measure of competitive dispersion based on a continuous outcome metric rather than binary win-loss outcomes.

5. **Mean Absolute Rank Change**: The conference-year mean of each team's absolute change in conference standings rank (based on overall win percentage) from the prior year. This provides an alternative measure of competitive balance based on the ordering of teams, rather than the deviation in performance across teams.

6. **Mean Absolute Conference Rank Change**: The conference-year mean of each team's absolute change in conference standings rank (based on conference win percent-

age) from the prior year. This provides an alternative measure of competitive balance based on the ordering of teams, rather than the deviation in performance across teams.

Table 2 reports the mean and standard deviation for all team-year outcome variables and conference-year outcome variables, by sport.[14]

4 Methods

The team-year regressions take the following form:

$$Y_{it} = \beta_1 Y_{i,t-1} + \beta_2 I(year \geq 2021) + \beta_3 I(year \geq 2021)^* Y_{i,t-1} + \beta_4 X_{it} + \alpha_i + \delta_t + \epsilon_{it}, \quad (1)$$

where Y_{it} is one of the four team-year outcomes described in Section 3, $Y_{i,t-1}$ is the lagged value for that outcome, X_{it} is the number of total teams in team i's conference in year t, α_i is a team fixed effect, δ_t is a year fixed effect, and ϵ_{it} is an idiosyncratic error term. The coefficient of interest is β_3, which measures the change in year-over-year team performance persistence after the NIL and transfer era began in 2021. Note that because of the year fixed effects, the $year \geq 2021$ indicator drops out of the model and β_2 is not identified, but the interaction between the $year \geq 2021$ indicator and the lagged team performance metric does not drop out and β_3 therefore is still identified.

The conference-year regressions take the following form:

$$Y_{ct} = \beta_1 I(year \geq 2021) + \beta_2 X_{ct} + \alpha_c + \epsilon_{ct}, \quad (2)$$

where Y_{ct} is one of the six team-year outcomes described in Section 3, X_{ct} is the number of teams in conference c and year t, α_c is a conference fixed effect, and ϵ_{ct} is an idiosyncratic

[14] The sample size for the conference winning percentage variables is smaller than the other variables due to dropping teams that do not belong to a conference and thus have no conference games. The sample size for the mean absolute rank change variables are even smaller due to dropping teams that do not belong to a conference combined with the change variable only existing beginning in 2011 in our dataset.

error term. The coefficient of interest is β_1, which measures the change in conference-year competitive balance outcomes after the NIL and transfer era began in 2021.

For both the team-year regressions and the conference-year regression, we estimate two sets of models for each sport: (1) the full sample and (2) a robustness check separating the Power 5 football conferences (SEC, Big Ten, Big 12, ACC, Pac- 12) or Power 6 basketball conferences (SEC, Big Ten, Big 12, ACC, Big East, Pac-12) from non-power conferences.[15] These subgroup analyses test whether competitive balance trends differ between the more versus less prestigious conferences and teams.

5 Results

5.1 All conferences combined

The results for team performance persistence are shown in Tables 3 and 4. For both college football and college basketball, we estimate that the NIL and transfer era are associated with a significant reduction in team performance persistence over time. The interaction between the lagged performance metric and the post-2021 indicator is negative and statistically significant for all four (three out of four) performance metrics for football (basketball). The reduction in persistence is economically meaningful. For example, in column (1) of Table 3 the baseline persistence estimate is 0.2872 and the interaction is -0.1257, which generates an implied post-2021 persistence of 0.1615 (44% reduction). Across the seven specifications with statistically significant reductions between the two sports, the magnitude of the reduction ranges between 17% and 44% of the baseline persistence coefficient for the lagged performance metric shown in the same column. The reduction in team performance persistence is larger in college football, both in absolute terms (the interaction coefficient estimate) and as a percentage of the baseline persistence parameter.

[15] We also performed a robustness check separating just the Big Ten and SEC from the other conferences. The results are similar to those that separate the whole set of power conferences and are available upon request.

The results for year-to-year conference standings mobility are shown in Tables 5 and 6. The tables report the difference in average absolute rank change in the NIL and transfer era, using both overall record rank and conference record rank. Both tables show a significant increase in average absolute rank change across teams in the NIL and transfer era. The magnitude is larger in football than basketball. Football shows an increase in average absolute rank change of approximately 0.3 rank spots, whereas basketball shows an increase of approximately 0.15-0.20 spots. The sample mean for the average absolute rank change is approximately 2.9 for football and 2.6 for basketball, as seen in Table 2, so these effects are relatively modest compared to the baseline level of standings mobility: approximately a 5-10% increase in mobility, depending on the sport.

The results for competitive balance in conference in a given year are shown in Tables 7 and 8. The tables report the change in the standard deviation of performance in a given year in the NIL and transfer era. Table 7 shows the results for college football. We estimate that the NIL and transfer era are associated with a significant improvement in all four competitive balance measures: the within-conference standard deviation of overall winning percentage, conference winning percentage, Simple Rating System, and margin of victory were all lower on average beginning in 2021. The magnitude of the coefficients is modest: each represents approximately a 5-12% reduction in standard deviation relative to the sample mean standard deviation of performance across conferences and years as shown in Table 2. Table 8 shows the results for college basketball. For basketball, there is no association between the NIL and transfer era and the competitive balance metrics: the sign of the coefficient for the NIL and transfer era is negative as with the college football results, but none of the coefficients approach statistical significance.

5.2 Power conferences

Next, we assess differential results by conference power, which is proxy for prestige and market power. For all of the previous analyses, we now estimate the regression models separately for teams in the Power 5 conferences and the non-Power 5 conferences (Power 6 for basketball). The team persistence results by conference power are shown in Tables 9 and 10. For football, the results show large and significant reductions in persistence for teams in Power 5 conferences, whereas teams in the non-Power 5 conferences show smaller and insignificant reductions. For basketball, both Power 6 and non-Power 6 teams show significant reductions in team persistence (win % and conference win % significant for Power 6; all four outcomes significant for non-Power 6), although the magnitude of the reductions in persistence for winning percentage and conference winning percentage are larger for Power 6 teams than non-Power 6 teams (in absolute terms and as a percentage of the baseline persistence parameter).

The year-to-year conference standings mobility results by conference power are shown in Tables 11 and 12. For football, the results show large and significant increases in average absolute rank change for Power 5 conferences (approximately 0.5 spots), whereas non-Power 5 conferences show smaller and insignificant increases. For basketball, both Power 6 and non-Power 6 conferences have moderately sized coefficients for the difference in average absolute rank change, but only the coefficient for non-Power 6 conference-game rankings is statistically significant.

Finally, the results for competitive balance within conference in a given year by conference power are shown in Tables 13 and 14. Non-Power 5 football conferences show a significant reduction in the standard deviation of performance across teams, whereas the other sports and conferences show no significant change (with the exception of SRS for Power 5 football, which shows a relatively small reduction that is statistically significant).

5.3 Robustness

One challenge for our results is separating the impact of NIL and the transfer era from conference realignment and the impact of COVID-19 disruptions. Several teams changed conferences in 2021 or later. This is a potential confounder for the team performance persistence models, as team persistence could change due to changes in the quality of opponents. It could also bias the conference standings rank mobility results, as an increase (decrease) in total number of teams means a larger (smaller) number of possible rank slots. In our primary models, we address this confounder by controlling for the total number of teams in a given conference each year.

To evaluate robustness to conference realignment, we re-estimated our team performance persistence models and standings rank mobility models after excluding all teams who switched conferences during the treatment window (2021 or later). These teams were excluded from the entire regression sample. For the standings rank mobility models, we also excluded conferences who had fewer than 5 teams in any given year. When computing the conference ranks, we ranked teams only relative to the set of teams left in the regression sample (i.e., excluding teams who switched conferences during 2021 or later).

The results are shown in Tables A1 through A4. The team performance persistence results are similar to the main results for both sports. The baseline persistence coefficient estimates and the post-2021 treatment coefficient estimates are both slightly smaller than the main results. This results in two of the four interaction coefficient estimates becoming statistically insignificant for football, but otherwise the patterns and conclusions are the same. The robustness results for conference rank mobility tell somewhat of a different story. The coefficient estimates for the effect of NIL and the transfer era in football become larger and are statistically significant at even higher levels, whereas the coefficient estimates for men's basketball become smaller and are no longer statistically significant. Overall, for team-level performance persistence, the robustness results do not support the possibility that the reduction in persistence found for both sports was driven by conference realignment. For standings rank mobility, the results suggest that conference alignment could be explaining a meaningful portion of the increase in standings mobility observed during the NIL and transfer era for men's basketball, but not for football.

COVID-19 is also a potential confounder. Student-athletes who competed during the

2020-2021 seasons were granted an extra year of eligibility. Many of these athletes spent their extra year of eligibility at a different university after graduating from their original institution. This extra supply of players could also have impacted our competitive balance metrics during the treatment window. More years of data will be needed to separate the effect of NIL and the transfer era from the temporary COVID-19 disruptions.

6 Conclusion

We analyze the change in competitive balance in college football and men's college basketball following the introduction of NIL and the loosening of transfer restrictions in 2021. Public opinion on the topic has been mixed and has evolved over time, with the early narrative being that it would make the "rich richer" and the more recent narrative being that it has leveled the playing field. Previous research suggests it has impacted the distribution of talent across teams, but with mixed results regarding the implications for competitive balance. Our paper provides a deeper investigation into competitive balance outcomes than prior work, while also analyzing the role of market power as an important moderator.

We find improvements in competitive balance for college football and men's college basketball. These improvements primarily appear in the form of increased year-to-year variability in team performance and conference standings order. The gap between top and bottom teams in a given year (regardless of who the teams are), on the other hand, appears relatively unchanged in the NIL and transfer era. For college football, the increase in year-to-year variability is driven entirely by teams in Power 5 conferences. Men's college basketball shows increases in year-to-year variability for Power 6 and non-Power 6 conference teams. Several of our results are stronger for football than men's basketball, and it appears that conference realignment may explain the increase in conference standings variability for men's basketball.

These results have important implications for the popularity of college athletics and the impact of athletics on universities as a whole. Outcome uncertainty is generally regarded as important for game attendance and television viewership (El-Hodiri and Quirk, 1971; Humphreys and Miceli, 2020; Rottenberg, 1956; Szymanski, 2003). College athletics have historically had lower levels of competitive uncertainty than professional sports (Eckard, 2019; Mills and Winfree, 2018). Our results suggest NIL and the transfer era have pushed college football and men's college basketball toward improved levels of standings uncertainty. Furthermore, the increase in competitive balance could provide more equitable opportunity for schools to access the widespread benefits associated with athletics success (Anderson, 2017; Meer and Rosen, 2009; Tabakovic and Wollmann, 2019). Future work should continue to assess competitive balance in college athletics as the rules evolve, teams settle into new norms, and we move further away from the temporary COVID-related disruptions.

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Figures and Tables

Table 1: Sample Sizes by Sport and Level of Analysis

	College Football	Men's Basketball
Team-Year Level		
Total team-years (all)	1,921	5,291
Team-years (regression sample)	1,782	4,923
Unique teams	135	368
Years covered (with lags)	2011-2024	2011-2024
Conference-Year Level		
Total conference-years	167	482
Conferences represented	13	34
Years covered	2010-2024	2010-2024

The table reports sample sizes for the datasets of analysis based on the web-scraped data from sports-reference.com. See Section 3 for more information.

Table 2: Summary Statistics

	College Football			Men's Basketball		
	Mean	SD	Obs.	Mean	SD	Obs.
Team-Year Variables						
Win Pct.	0.519	0.219	1,782	0.512	0.172	4,923
Conf. Win Pct.	0.500	0.262	1,705	0.500	0.210	4,901
SRS	0.872	9.878	1,782	−0.571	10.187	4,923
MOV	1.491	11.031	1,782	−0.315	6.446	4,923
Conference-Year Variables						
SD of Win Pct.	0.224	0.042	167	0.168	0.033	482
SD of Conf. Win Pct.	0.273	0.034	152	0.219	0.037	478
SD of SRS	8.321	2.081	167	5.989	1.553	482
SD of MOV	11.010	3.034	167	5.883	1.527	482
Mean Abs Rank Change (Overall)	2.846	0.858	140	2.567	0.923	445
Mean Abs Rank Change (Conf.)	2.872	0.847	140	2.575	0.924	445

Statistics computed using regression samples (complete cases). Team-year variables: mean and SD across team-year observations with lagged data (2011-2024). Conference-year variables: mean and SD of within-conference standard deviations (or mean absolute rank changes) across conference-year observations. Conference win percentage models have fewer observations due to dropping independent teams that do not belong to a conference and thus have no conference games. Mean absolute rank change models have fewer observations due to dropping independent teams and due to the regression sample beginning in 2011 instead of 2010. SRS = Simple Rating System; MOV = margin of victory.

Table 3: College Football Team Performance Persistence

	Win%	Conf Win%	SRS	MOV
Lagged Win%	0.2872***			
	(0.0272)			
Lagged Conf Win%		0.2410***		
		(0.0285)		
Lagged SRS			0.3170***	
			(0.0258)	
Lagged MOV				0.3510***
				(0.0245)
Lagged × Post-2021	-0.1257***	-0.1026**	-0.0710**	-0.0921**
	(0.0442)	(0.0499)	(0.0356)	(0.0410)
Conference size control	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1782	1705	1782	1782
Adjusted R^2	0.344	0.288	0.594	0.426

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
The table reports the change in team performance persistence in the NIL and portal era. The coefficients for the lagged performance metrics report the baseline level of persistence, while the interaction reports the change in the NIL and portal era. *Win%* stands for overall winning percentage for the season. *Conf Win%* stands for winning percentage in conference games. *SRS* stands for Simple Rating System. *MOV* stands for average margin of victory. *Lagged x Post-2021* is the interaction between the lagged metric used in that column and the post-2021 time period. Standard errors clustered at team level shown in parentheses.

Table 4: College Basketball Team Performance Persistence

	Win%	Conf Win%	SRS	MOV
Lagged Win%	0.2997***			
	(0.0178)			
Lagged Conf Win%		0.2731***		
		(0.0179)		
Lagged SRS			0.3807***	
			(0.0185)	
Lagged MOV				0.3538***
				(0.0188)
Lagged $\times$ Post-2021	-0.0804***	-0.0624**	-0.0092	-0.0635**
	(0.0261)	(0.0278)	(0.0184)	(0.0263)
Conference size control	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4923	4901	4923	4923
Adjusted R^2	0.396	0.328	0.794	0.520

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
The table reports the change in team performance persistence in the NIL and portal era. The coefficients for the lagged performance metrics report the baseline level of persistence, while the interaction reports the change in the NIL and portal era. *Win%* stands for overall winning percentage for the season. *Conf Win%* stands for winning percentage in conference games. *SRS* stands for Simple Rating System. *MOV* stands for average margin of victory. *Lagged x Post-2021* is the interaction between the lagged metric used in that column and the post-2021 time period. Standard errors clustered at team level shown in parentheses.

Table 5: College Football Conference Standings Rank Mobility

	Mean Abs Rank Change (Overall)	Mean Abs Rank Change (Conf)
Year $\geq$ 2021	0.3165*	0.3240**
	(0.1692)	(0.0445)
Conference size control	Yes	Yes
Conference FE	Yes	Yes
Observations	140	140
Adjusted R^2	0.277	0.329

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
The table reports the difference in mean absolute rank change in the NIL and transfer era. Mean absolute rank change is absolute change in a team's conference standings rank from the previous year, averaged across teams. Standard errors clustered at conference level shown in parentheses.

Table 6: College Basketball Conference Standings Rank Mobility

	Mean Abs Rank Change (Overall)	Mean Abs Rank Change (Conf)
Year $\geq$ 2021	0.1571*	0.1947**
	(0.0901)	(0.0925)
Conference size control	Yes	Yes
Conference FE	Yes	Yes
Observations	445	445
Adjusted R^2	0.360	0.377

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
The table reports the difference in mean absolute rank change in the NIL and transfer era. Mean absolute rank change is absolute change in a team's conference standings rank from the previous year, averaged across teams. Standard errors clustered at conference level shown in parentheses.

Table 7: College Football Imbalance Within Conference-Year

	SD Win%	SD Conf Win%	SD SRS	SD MOV
Year $\geq$ 2021	-0.0137***	-0.0127***	-0.7722***	-1.2807***
	(0.0043)	(0.0047)	(0.1782)	(0.4233)
Conference size control	Yes	Yes	Yes	Yes
Conference FE	Yes	Yes	Yes	Yes
Observations	167	152	167	167
Adjusted R^2	0.144	0.165	0.445	0.097

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
The table reports the change in competitive imbalance within conferences in the NIL and transfer era. *SD Win%* is the standard deviation of overall winning percentage across teams in that conference-year. *SD Conf Win%* is the standard deviation of conference winning percentage across teams in that conference-year. *SD SRS* is the standard deviation of Simple Rating System scores across teams in that conference-year. *SD MOV* is the standard deviation of margin of victory across teams in that conference-year. Standard errors clustered at conference level shown in parentheses.

Table 8: College Basketball Imbalance Within Conference-Year

	SD Win%	SD Conf Win%	SD SRS	SD MOV
Year $\geq$ 2021	-0.0023	-0.0013	-0.1441	-0.1277
	(0.0037)	(0.0037)	(0.1578)	(0.1631)
Conference size control	Yes	Yes	Yes	Yes
Conference FE	Yes	Yes	Yes	Yes
Observations	482	478	482	482
Adjusted R^2	0.123	0.174	0.261	0.194

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
The table reports the change in competitive imbalance within conferences in the NIL and transfer era. *SD Win%* is the standard deviation of overall winning percentage across teams in that conference-year. *SD Conf Win%* is the standard deviation of conference winning percentage across teams in that conference-year. *SD SRS* is the standard deviation of Simple Rating System scores across teams in that conference-year. *SD MOV* is the standard deviation of margin of victory across teams in that conference-year. Standard errors clustered at conference level shown in parentheses.

Table 9: CFB Team Persistence: Power 5 vs Non-Power 5

	Power 5				Non-Power 5			
	Win%	Conf Win%	SRS	MOV	Win%	Conf Win%	SRS	MOV
Lagged Win%	0.2506***				0.2955***			
	(0.0446)				(0.0366)			
Lagged Conf Win%		0.1811***				0.2657***		
		(0.0421)				(0.0394)		
Lagged SRS			0.3433***				0.3115***	
			(0.0416)				(0.0316)	
Lagged MOV				0.3289***				0.3606***
				(0.0411)				(0.0311)
Lagged × Post-2021	-0.1892***	-0.1881***	-0.1537***	-0.1406**	-0.0720	-0.0172	-0.0778	-0.0679
	(0.0620)	(0.0654)	(0.0542)	(0.0616)	(0.0651)	(0.0761)	(0.0524)	(0.0558)
Conference size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	892	890	892	892	890	815	890	890
Adjusted R^2	0.356	0.346	0.478	0.432	0.302	0.242	0.411	0.370

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

The table reports the change in team performance persistence in the NIL and transfer era separately for teams in Power 5 versus non-Power 5 conferences. Other model details can be found in the footnote for Table 3, which combined all teams together. Standard errors clustered at team level shown in parentheses.

Table 10: MCBB Team Persistence: Power 6 vs Non-Power 6

	Power 6				Non-Power 6			
	Win%	Conf Win%	SRS	MOV	Win%	Conf Win%	SRS	MOV
Lagged Win%	0.2670***				0.3038***			
	(0.0412)				(0.0199)			
Lagged Conf Win%		0.2240***				0.2832***		
		(0.0382)				(0.0204)		
Lagged SRS			0.3558***				0.3900***	
			(0.0416)				(0.0215)	
Lagged MOV				0.3177***				0.3643***
				(0.0425)				(0.0215)
Lagged × Post-2021	-0.1466**	-0.1166*	-0.0375	-0.0548	-0.0616**	-0.0525*	-0.0414*	-0.0777**
	(0.0634)	(0.0623)	(0.0572)	(0.0574)	(0.0291)	(0.0316)	(0.0250)	(0.0304)
Conference size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1059	1059	1059	1059	3864	3842	3864	3864
Adjusted R^2	0.313	0.323	0.459	0.372	0.375	0.327	0.678	0.482

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

The table reports the change in team performance persistence in the NIL and transfer era separately for teams in Power 6 versus non-Power 6 conferences. Other model details can be found in the footnote for Table 4, which combined all teams together. Standard errors clustered at team level shown in parentheses.

Table 11: College Football Standings Mobility: Power 5 vs Non-Power 5

	Power 5		Non-Power 5	
	Mean Abs Rank Change (Overall)	Mean Abs Rank Change (Conf)	Mean Abs Rank Change (Overall)	Mean Abs Rank Change (Conf)
Year $\geq$ 2021	0.4847**	0.5408***	0.1809	0.1858
	(0.2201)	(0.1516)	(0.2223)	(0.1937)
Conference size control	Yes	Yes	Yes	Yes
Conference FE	Yes	Yes	Yes	Yes
Observations	69	69	71	71
Adjusted R^2	0.291	0.345	0.232	0.288

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
The table reports the difference in mean absolute rank change in the NIL and transfer era, separately by Power 5 and non-Power 5 conferences. Other model details can be found in the footnote for Table 5, which combined all conferences together. Standard errors clustered at conference level shown in parentheses.

Table 12: College Basketball Standings Mobility: Power 6 vs Non-Power 6

	Power 6		Non-Power 6	
	Mean Abs Rank Change (Overall)	Mean Abs Rank Change (Conf)	Mean Abs Rank Change (Overall)	Mean Abs Rank Change (Conf)
Year $\geq$ 2021	0.3566	0.1490	0.1078	0.2000**
	(0.2522)	(0.2719)	(0.0914)	(0.0934)
Conference size control	Yes	Yes	Yes	Yes
Conference FE	Yes	Yes	Yes	Yes
Observations	83	83	362	362
Adjusted R^2	0.233	0.229	0.361	0.387

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
The table reports the difference in mean absolute rank change in the NIL and transfer era, separately by Power 6 and non-Power 6 conferences. Other model details can be found in the footnote for Table 6, which combined all conferences together. Standard errors clustered at conference level shown in parentheses.

Table 13: College Football Conference-Year Imbalance: Power 5 vs Non-Power 5

	Power 5 Conferences				Non-Power 5 Conferences			
	SD Win%	SD Conf Win%	SD SRS	SD MOV	SD Win%	SD Conf Win%	SD SRS	SD MOV
Year $\geq$ 2021	-0.0071	-0.0057	-0.5278**	-0.7618	-0.0182***	-0.0195***	-0.9323***	-1.5091**
	(0.0071)	(0.0046)	(0.2551)	(0.6785)	(0.0050)	(0.0066)	(0.2164)	(0.6055)
Conference size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conference FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74	74	74	74	93	78	93	93
Adjusted R^2	0.109	0.126	0.175	0.067	0.097	0.158	0.462	0.093

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

The table reports the change in competitive imbalance within conferences in the NIL and transfer era, separately by Power 5 and non-Power 5 conferences. Other model details can be found in the footnote for Table 7, which combined all conferences together. Standard errors clustered at conference level shown in parentheses.

Table 14: College Basketball Conference-Year Imbalance: Power 6 vs Non-Power 6

	Power 6 Conferences				Non-Power 6 Conferences			
	SD Win%	SD Conf Win%	SD SRS	SD MOV	SD Win%	SD Conf Win%	SD SRS	SD MOV
Year $\geq$ 2021	0.0046	-0.0015	0.0664	0.1901	-0.0038	-0.0014	-0.1868	-0.1952
	(0.0102)	(0.0132)	(0.4426)	(0.4276)	(0.0038)	(0.0037)	(0.1675)	(0.1748)
Conference size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conference FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	89	89	89	89	393	389	393	393
Adjusted R^2	-0.016	-0.026	-0.035	-0.048	0.114	0.184	0.298	0.216

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
The table reports the change in competitive imbalance within conferences in the NIL and transfer era, separately by Power 6 and non-Power 6 conferences. Other model details can be found in the footnote for Table 8, which combined all conferences together. Standard errors clustered at conference level shown in parentheses.

Appendix

Table A1: College Football Team Performance Persistence – Excluding Conference Switchers

	Win%	Conf Win%	SRS	MOV
Lagged Win Pct	0.2730***			
	(0.0319)			
Lagged Conf Win Pct		0.2292***		
		(0.0329)		
Lagged SRS			0.2919***	
			(0.0275)	
Lagged MOV				0.3456***
				(0.0284)
Lagged × Post-2021	-0.1126**	-0.1069*	-0.0467	-0.0772
	(0.0519)	(0.0555)	(0.0409)	(0.0488)
Conference size control	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1371	1338	1371	1371
Adjusted R^2	0.361	0.305	0.602	0.448

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Models are the same as those reported in Table 3, except dropping teams that switched conferences in 2021 or later. Excluded teams were: Arizona, Arizona State, Army, BYU, California, Charlotte, Cincinnati, Colorado, Florida Atlantic, Houston, Liberty, Marshall, New Mexico State, North Texas, Oklahoma, Old Dominion, Oregon, Oregon State, Rice, SMU, Southern Mississippi, Stanford, Texas, UAB, UCF, UCLA, USC, UTSA, Utah, Washington, Washington State.

Table A2: College Basketball Team Performance Persistence – Excluding Conference Switchers

	Win%	Conf Win%	SRS	MOV
Lagged Win Pct	0.2949***			
	(0.0199)			
Lagged Conf Win Pct		0.2674***		
		(0.0202)		
Lagged SRS			0.3782***	
			(0.0195)	
Lagged MOV				0.3434***
				(0.0204)
Lagged × Post-2021	-0.0673**	-0.0498*	-0.0098	-0.0473*
	(0.0282)	(0.0297)	(0.0202)	(0.0266)
Conference size control	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4136	4120	4136	4136
Adjusted R^2	0.397	0.332	0.799	0.519

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Models are the same as those reported in Table 4, except dropping teams that switched conferences in 2021 or later. Excluded teams were: Arizona, Arizona State, Austin Peay, Belmont, Brigham Young, Bryant, California, Campbell, Charlotte, Chicago State, Cincinnati, Colorado, Florida Atlantic, Hampton, Hartford, Houston, Illinois-Chicago, Jacksonville State, James Madison, Kennesaw State, Lamar, Liberty, Little Rock, Loyola (IL), Marshall, Merrimack, Monmouth, Mount St. Mary's, Murray State, New Mexico State, North Carolina A&T, North Texas, Oklahoma, Old Dominion, Oregon, Oregon State, Rice, Sacred Heart, Sam Houston, Southern California, Southern Methodist, Southern Mississippi, Southern Utah, Stanford, Stephen F. Austin, Stony Brook, Texas, Texas-Rio Grande Valley, UAB, UCF, UCLA, UT Arlington, UTSA, Utah, Washington, Washington State, Western Illinois.

Table A3: College Football Conference Standings Rank Mobility – Excluding Conference Switchers

	Mean Abs Rank Change (Overall)	Mean Abs Rank Change (Conf)
Year $\geq$ 2021	0.5045***	0.4964***
	(0.1185)	(0.1309)
Conference size control	Yes	Yes
Conference FE	Yes	Yes
Observations	112	112
Adjusted R^2	0.515	0.582

Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Models are the same as those reported in Table 5, except dropping teams that switched conferences in 2021 or later and dropping conferences with missing years or fewer than five teams in a given year. Ranks were re-calculated using only teams that remained in the same conference 2021-2024. Excluded teams were: Arizona, Arizona State, Army, BYU, California, Charlotte, Cincinnati, Colorado, Florida Atlantic, Houston, Liberty, Marshall, New Mexico State, North Texas, Oklahoma, Old Dominion, Oregon, Oregon State, Rice, SMU, Southern Mississippi, Stanford, Texas, UAB, UCF, UCLA, USC, UTSA, Utah, Washington, Washington State.

Table A4: College Basketball Conference Standings Rank Mobility – Excluding Conference Switchers

	Mean Abs Rank Change (Overall)	Mean Abs Rank Change (Conf)
Year $\geq$ 2021	0.0801	0.1505
	(0.0995)	(0.1020)
Conference size control	Yes	Yes
Conference FE	Yes	Yes
Observations	406	406
Adjusted R^2	0.376	0.382

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at conference level shown in parentheses

Models are the same as those reported in Table 6, except dropping teams that switched conferences in 2021 or later and dropping conferences with missing years or fewer than five teams in a given year. Ranks were re-calculated using only teams that remained in the same conference 2021-2024. Excluded team were: Arizona, Arizona State, Austin Peay, Belmont, Brigham Young, Bryant, California, Campbell, Charlotte, Chicago State, Cincinnati, Colorado, Florida Atlantic, Hampton, Hartford, Houston, Illinois-Chicago, Jacksonville State, James Madison, Kennesaw State, Lamar, Liberty, Little Rock, Loyola (IL), Marshall, Merrimack, Monmouth, Mount St. Mary's, Murray State, New Mexico State, North Carolina AT, North Texas, Oklahoma, Old Dominion, Oregon, Oregon State, Rice, Sacred Heart, Sam Houston, Southern California, Southern Methodist, Southern Mississippi, Southern Utah, Stanford, Stephen F. Austin, Stony Brook, Texas, Texas-Rio Grande Valley, UAB, UCF, UCLA, UT Arlington, UTSA, Utah, Washington, Washington State, Western Illinois.