



Competitive balance in the NIL era: recruiting redistribution and stability in the revenue–performance relationship

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Abstract

The introduction of name, image, and likeness (NIL) compensation has substantially altered the economic environment of NCAA Division I Football Bowl Subdivision (FBS) football, but whether this change has modified the relationship between program financial strength, recruiting distribution, and on-field performance remains unclear. This study evaluates these relationships by comparing pre-NIL (2017) and post-NIL (2025) FBS seasons using estimated game-day ticket revenue, Simple Rating System (SRS) performance, and team recruiting-point totals.

Logarithmic regression identified a strong diminishing-returns relationship between estimated revenue and SRS in both periods, with coefficients of determination of 0.5001 in 2017 and 0.5512 in 2025. Despite the apparent increase in explanatory power, a Chow test found no statistically significant structural difference between the two regression relationships ($F = 0.304$, $p = 0.738$), while bootstrap analyses likewise showed that the observed differences in both R^2 and regression slope were consistent with sampling variation. Thus, the association between estimated financial strength and on-field performance remained statistically stable across the two periods examined. A different pattern emerged for recruiting. The Gini coefficient for recruiting-point totals decreased from 0.1767 in 2017 to 0.1451 in 2025, with a bootstrapped 95% confidence interval for the difference of $[-0.057, -0.005]$, indicating a statistically significant broadening of recruiting-point distribution across FBS programs. Together, these findings reveal an important distinction between competitive inputs and realized competitive outcomes in the NIL era: recruiting value became more evenly distributed across programs without a detectable corresponding change in the relationship between estimated revenue and on-field performance. Rather than demonstrating that NIL has already equalized competitive performance, the results suggest that its more readily detectable association may lie upstream, in the distribution of recruiting resources. This separation between recruiting redistribution and performance stability provides a quantitative framework for evaluating how major changes in collegiate athlete compensation may propagate through competitive systems over time.

Keywords

Name, Image, and Likeness (NIL), NCAA football, College football, Competitive balance, Recruiting, Recruiting concentration, Gini coefficient, Athletic performance, Sports economics, Collegiate athletics

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1. Introduction

The introduction of name, image, and likeness (NIL) compensation in 2021 represented a major change in the economic structure of NCAA Division I football. By allowing collegiate athletes to receive compensation associated with their name, image, and likeness, NIL introduced new financial opportunities into a competitive environment in which programs already differed substantially in revenue, resources, recruiting strength, and on-field success. This change raises an important question: has the post-NIL era altered competitive balance in college football, and if so, where is that change most readily observed?

Competitive balance can be considered at multiple stages of the collegiate football system. Financial resources may be associated with on-field performance, while recruiting determines how incoming talent is distributed among programs. A change in one relationship does not necessarily imply a corresponding change in the other. Evaluating NIL-era football therefore requires distinguishing between the distribution of competitive inputs, such as recruiting strength, and realized outcomes, such as team performance.

This study compares the 2017 pre-NIL and 2025 post-NIL FBS seasons using two complementary analyses. First, estimated game-day ticket revenue is related to Simple Rating System (SRS) performance to examine whether the financial strength–performance relationship differs between the two periods. Second, the distribution of team recruiting-point totals is evaluated using the Gini coefficient to determine whether recruiting became more or less concentrated across FBS programs. Together, these analyses provide a quantitative

framework for examining whether the transition to the NIL era coincided with measurable changes in different dimensions of competitive balance.

2. Methods

2.1 Two period design

To evaluate potential changes associated with the introduction of NIL, the study required clearly defined pre- and post-NIL comparison periods. NIL was introduced in NCAA football in July 2021, but the years immediately following its implementation represented a period of transition during which programs may have differed in the rate at which they adapted to the new environment. Accordingly, 2025 was selected as the post-NIL comparison year to allow sufficient time for NIL practices to become broadly established across FBS programs. This approach reduces the influence of the initial implementation period from 2022–2024, when adoption and integration may have been less uniform across programs.

Selection of the pre-NIL comparison year required additional consideration because the years immediately preceding NIL were not suitable for establishing a representative baseline. The 2020 season was substantially disrupted by the COVID-19 pandemic, particularly with respect to stadium attendance and game-day revenue, making it unsuitable for comparison with a conventional season. The 2021 season was also excluded because NIL regulations took effect on July 1, 2021, making it a transitional rather than a clearly pre-NIL period. Accordingly, 2017 was selected as the pre-NIL comparison year, providing temporal symmetry with 2025 around the 2021 introduction of NIL.

The selection of 2017 also reduces the potential influence of anticipatory changes in program behavior as NIL became increasingly foreseeable in the years immediately preceding its implementation. Thus, 2017 serves as a proxy for the relatively stable pre-NIL period, while 2025 represents a more established post-NIL environment. Importantly, this two-period design should not be interpreted as a natural experiment capable of establishing a causal effect of NIL. Comparison of 2017 and 2025 can identify differences between representative pre- and post-NIL seasons, but it cannot establish a longitudinal trend or distinguish NIL-associated changes from other temporal changes occurring in collegiate football over the same period.

2.2 Data choice

Selection of the study variables was guided by the objective of comparing the relationship between financial resources and athletic performance across the pre- and post-NIL periods. A single primary financial predictor and performance outcome were used to provide a consistent and readily interpretable comparison between 2017 and 2025. Average attendance was selected as the basis for the financial variable because, when combined with estimated ticket prices, it permits calculation of an ~ game-day ticket revenue for each program. This measure provides a standardized proxy for program financial strength, although it does not represent total athletic-department revenue or NIL expenditures. Attendance data for 2017 were obtained from the NCAA Official Attendance Records (1), while 2025 attendance data were obtained from the D1 Ticker FBS Attendance Trends dataset (2).

Quantifying athletic performance requires a measure that accounts for differences in both

game outcomes and schedule difficulty. Win percentage or point differential alone may provide an incomplete assessment because teams face schedules of varying strength, while strength of schedule alone does not capture how effectively a team performs against its opponents. Accordingly, the Simple Rating System (SRS) was selected as the primary measure of on-field performance. SRS incorporates average point differential and strength of schedule into a single rating, allowing team performance to be evaluated relative to the broader competitive field. An SRS of 0.00 represents ~ average performance, while positive or negative values indicate performance above or below the overall average, respectively. By integrating margin of victory with schedule strength, SRS provides a standardized outcome variable suitable for comparing FBS programs across the two study periods. SRS data for the 2017 and 2025 seasons were obtained from Sports Reference College Football and combined with the corresponding attendance and estimated ticket-revenue data (3,4).

Ticket-price inflation between 2017 and 2025 was also considered when constructing the financial variable. Because applying a uniform inflation adjustment would rescale the revenue variable without altering the underlying regression fit or coefficient of determination, no additional inflation multiplier was applied. This approach avoids introducing an additional estimated parameter into an already ~ ticket-pricing measure and maintains consistency in the construction of the revenue variable across programs.

The composition of the FBS also differed between the two comparison years. Several

programs—including JMU, Liberty, Coastal Carolina, Jacksonville State, Delaware, Sam Houston State, Missouri State, and Kennesaw State—were not members of the NCAA Division I FBS in 2017 but were included in the 2025 dataset. In addition, several programs changed conference affiliation between the two periods. Consequently, the 2017 and 2025 samples are not identical in program composition or conference membership. For each season, programs were classified according to their conference affiliation in that respective year.

2.3 Tiered ticket pricing

To estimate average game-day ticket revenue for each program in 2017 and 2025, conference affiliation was incorporated into the ticket-price assumptions. Because ticket prices vary systematically across conferences with different levels of demand, attendance, and market prominence, a tiered pricing framework was used rather than assigning a single uniform ticket price to all FBS programs. Within each conference, programs were assigned the same representative average ticket price. These conference-level estimates were derived from ticket-selling platforms, published studies, and general reports describing conference-level ticket-pricing patterns.

For 2017, the representative average ticket prices were estimated at ~ \$125 for the SEC, \$105 for the Big Ten, \$80 for the Big 12, \$80 for the Pac-12, \$73 for the ACC, and \$50 for the Group of 4 conferences, including the Mountain West, MAC, Sun Belt, and American. For 2025, the corresponding estimates were ~ \$125 for the SEC, \$105 for the Big Ten, \$80 for the Big 12, \$73 for the ACC, and \$50 for the Group of 5

conferences, including the Mountain West, MAC, Sun Belt, Pac-12, and American.

The treatment of the Pac-12 differed between the two comparison years because its competitive and financial position changed substantially over the study period. In 2017, the Pac-12 was treated as a Power Five conference and assigned the higher conference-level ticket-price estimate of \$80. By 2025, following major conference realignment, the remaining Pac-12 programs were grouped with the lower-priced Group of 5 category for purposes of the revenue proxy.

Independent programs were generally assigned an estimated average ticket price of \$40 in both years. Two exceptions were applied. Notre Dame, which remained independent in both 2017 and 2025 and has substantially greater ticket demand than most independent programs, was assigned an estimated average ticket price of \$120, consistent with the ~ \$100–\$140 range used in constructing the pricing estimate. BYU, which was independent in 2017 and has a comparatively large regional fan base and stronger ticket demand than most independent programs, was assigned an estimated average ticket price of \$65 for the 2017 analysis.

These values should be interpreted as standardized conference-level pricing estimates rather than exact school-specific ticket prices. The purpose of the tiered framework is to provide a consistent basis for constructing the estimated game-day revenue variable across FBS programs, while recognizing that actual ticket prices can vary substantially among programs within the same conference.

2.4 Model domain

For both logarithmic models, the domain was defined as $X \in [0.25, 140]$, where X represents estimated average game-day ticket revenue in units of \$100,000. The lower bound was selected to accommodate programs with comparatively low attendance and ticket revenue; some Group of 5 programs, for example, fall near $X \in [2, 3]$. A lower bound of $X = 0.25$ therefore corresponds to \$25,000 in estimated game-day ticket revenue and provides sufficient coverage of the lower end of the observed and plausible revenue range.

The upper bound was selected to reflect the substantially greater revenues generated by high-attendance programs while avoiding extrapolation far beyond the range relevant to the present analysis. Because the model represents average game-day ticket revenue rather than revenue from individual high-profile games, an upper bound of $X = 140$, corresponding to \$14 million per game, was considered sufficiently broad for the modeled range. Accordingly, $X \in [0.25, 140]$ was used as the domain for both logarithmic models.

This domain should be interpreted as a practical modeling range rather than an absolute limit on possible game-day revenue. Programs with exceptionally large and established fan bases, such as Michigan or Ohio State, could potentially exceed the upper bound, particularly as ticket prices and college football revenues increase over time. The selected domain therefore defines the range over which the models are evaluated in this study rather than asserting that values outside this interval cannot occur.

2.5 Statistical comparison of Pre- and Post-NIL models

Although the 2017 and 2025 regression models produced different coefficients of determination and slopes, these numerical differences do not necessarily indicate a change in the underlying revenue–performance relationship. The 2017 model yielded $R^2 = 0.5001$ and a slope coefficient of 7.9894, whereas the 2025 model yielded $R^2 = 0.5512$ and a slope coefficient of 7.5526. Because both estimates were obtained from finite samples ($n = 128$ programs in 2017 and $n = 136$ programs in 2025), some of the observed differences could arise from sampling variation. A Chow test was therefore used to determine whether the two periods were better represented by statistically distinct regression relationships or by a common relationship.

The Chow test compared unrestricted and restricted representations of the data. In the unrestricted approach, separate regression models were fitted independently to the 2017 and 2025 datasets, allowing each period to have its own intercept and slope. Although the fitted relationships are logarithmic in revenue, the models are linear in the transformed predictor $\ln(X)$; therefore, the Chow test was applied to the intercept and coefficient of $\ln(X)$ in the corresponding linear-in-parameters regression specification. For each program, the residual was calculated as the difference between the observed SRS and the SRS predicted by the corresponding regression model. The residuals were squared and summed to obtain the sum of squared residuals (SSR) for each period, denoted $SSR_{(2017)}$ and $SSR_{(2025)}$. The combined error for the unrestricted model was therefore obtained from the sum of the two period-specific SSR values.

For the restricted model, the 2017 and 2025 observations were combined into a pooled dataset containing 264 team-season observations, with most programs represented in both years. A single regression model was then fitted to the pooled dataset, constraining the observations from both periods to share a common intercept and slope. Residuals were calculated and squared in the same manner as for the unrestricted models, and their sum was denoted SSR_{pooled} . Comparison of the residual error from the restricted and unrestricted models was then used to test whether allowing separate regression relationships for 2017 and 2025 produced a statistically significant improvement in model fit.

A bootstrap resampling procedure was additionally implemented to assess the robustness of the cross-period comparison. Using a custom Python script, observations were randomly sampled with replacement within each year's dataset while preserving the original sample sizes of 128 observations for 2017 and 136 observations for 2025. Because sampling was performed with replacement, an individual program could appear multiple times within a bootstrap sample, while other programs might not appear in that iteration. For each resampled dataset, the regression models were refitted and the corresponding R^2 values and slope coefficients were recorded.

This procedure was repeated 5,000 times, generating empirical distributions of plausible R^2 and slope differences under repeated resampling of the observed data. Bootstrap 95% confidence intervals were obtained using the percentile method by excluding the lowest and highest 2.5% of the resulting distributions.

These intervals were then used alongside the Chow test to evaluate whether the observed differences in model fit and slope between 2017 and 2025 were greater than would be expected from sampling variability.

2.6 Recruiting concentration analysis

In addition to examining the relationship between estimated financial strength and on-field performance, this study evaluated whether the distribution of recruiting strength across FBS programs differed between the pre- and post-NIL periods. NIL may influence the recruiting environment by expanding the financial opportunities available to collegiate athletes and potentially altering the set of programs capable of competing for recruits. To examine this dimension of competitive balance, recruiting concentration was compared between 2017 and 2025 using each program's total recruiting points for the respective season. Recruiting-point data for 2017 and 2025 were obtained from 247Sports (5,6).

Recruiting concentration was quantified using the Gini coefficient, a measure of inequality that ranges from 0 to 1. A value approaching 0 indicates a more even distribution of the measured resource across the population, whereas a value approaching 1 indicates progressively greater concentration among a smaller proportion of the population. Applied to the present analysis, a higher Gini coefficient indicates that recruiting-point totals are more concentrated among fewer FBS programs, while a lower coefficient indicates that recruiting-point totals are distributed more evenly across programs. The Gini coefficient therefore provides a standardized measure with which to compare the overall distribution of recruiting strength between the two study periods.

Importantly, the Gini coefficient in this analysis describes the distribution of aggregate program recruiting-point totals, rather than the distribution or movement of individual recruits. Recruiting-point totals incorporate information about the strength of a program's recruiting class, and elite recruits may contribute substantially to those totals; however, the analysis does not directly determine which programs acquired the highest-rated individual recruits, whether particular recruits moved between categories of programs, or whether the distribution of elite recruits specifically became more or less concentrated. Accordingly, changes in the Gini coefficient are interpreted as changes in the concentration of program-level recruiting-point totals rather than direct evidence of redistribution of individual or elite recruiting talent.

For each season, the recruiting-point totals of all included FBS programs were ordered from lowest to highest, and the cumulative sum of recruiting points was calculated across the ordered observations. The Gini coefficient was then calculated as, $G = \frac{(n+1)(\bar{k}) - 2 \sum(s)}{n \cdot k}$ (eq.1), where n is the number of programs included in the respective season ($n = 128$ in 2017 and $n = 136$ in 2025), k is the sum of all recruiting-point totals in that season, and s represents the cumulative recruiting-point totals across the ordered observations. This procedure yields a single Gini coefficient for each year, permitting direct comparison of recruiting-point concentration between the pre- and post-NIL samples.

Lorenz curves were also constructed to provide a graphical representation of recruiting-point

concentration. Programs were ordered according to recruiting-point totals, and the cumulative proportion of programs was compared with the cumulative proportion of total recruiting points. A distribution closer to the line of perfect equality indicates a more even allocation of recruiting points across programs, whereas greater deviation from this line indicates greater concentration. The Lorenz curves therefore provide a visual complement to the numerical Gini coefficients.

To quantify uncertainty in the difference between the 2017 and 2025 Gini coefficients, an automated bootstrap resampling procedure was implemented in Python. Programs were randomly sampled with replacement within each year's dataset while preserving the original sample sizes of 128 programs for 2017 and 136 programs for 2025. A Gini coefficient was recalculated for each resampled dataset, and the difference between the 2025 and 2017 coefficients was recorded for each iteration. This procedure was repeated 5,000 times to generate an empirical bootstrap distribution of the cross-period difference in recruiting concentration. A 95% confidence interval was then obtained using the percentile method by excluding the lowest and highest 2.5% of the bootstrap distribution. The resulting interval was used to determine whether the observed difference in recruiting-point concentration between 2017 and 2025 was distinguishable from sampling variability.

3. Results

The fitted regression equation for the 2017 model is, $f(X) = 7.9894 \ln(X) - 24.178$ (eq.2). Among the functional forms evaluated, including linear, exponential, step, and higher-

order polynomial models, the logarithmic model produced the highest coefficient of determination and therefore provided the best fit to the observed 2017 data. The shape of this relationship is consistent with diminishing marginal returns: as estimated game-day ticket revenue increases, equivalent additional increments in revenue are associated with progressively smaller increases in predicted SRS. Thus, differences in estimated financial resources are associated with larger predicted performance differences among lower-revenue programs than among programs already operating at comparatively high revenue levels. Importantly, this represents a diminishing marginal association within the fitted model and should not be interpreted as demonstrating that additional revenue or expenditure itself causes a corresponding improvement in athletic performance.

Another informative feature of the 2017 regression is the estimated revenue level corresponding to average predicted performance. This break-even point is obtained by setting the fitted function equal to zero, $f(X)=0$. Substituting Eq. 2 and solving for X gives, $7.9894\ln(X)-24.178=0$ and $X\approx 20.62$.

Because X represents estimated average game-day ticket revenue in units of \$100,000, $X\approx 20.62$ corresponds to $\sim \$2.062$ million. At this estimated revenue level, the fitted model

predicts an SRS of 0, representing $\sim$ average performance within the FBS comparison.

The first derivative of the fitted function provides a quantitative measure of the marginal relationship between estimated revenue and predicted SRS. For the 2017 model, $f'(X)=X7.9894$ (eq.3). Because $f'(X)$ decreases as X increases, an equivalent incremental increase in estimated revenue is associated with a progressively smaller increase in predicted SRS at higher revenue levels. Representative values of this marginal association are presented in Table 1.

This diminishing-return pattern is important for interpreting the fitted relationship. Although higher estimated revenue is associated with higher predicted SRS, the relationship is not proportional: the regression curve progressively flattens as revenue increases. Consequently, an additional increment of estimated revenue corresponds to a larger difference in predicted SRS among lower-revenue programs than among programs already situated at the upper end of the revenue distribution. The model therefore suggests that increasing financial strength is associated with progressively smaller marginal differences in predicted athletic performance, while still allowing individual programs to substantially outperform or underperform their model-predicted values.

Table 1. Marginal association between estimated game-day ticket revenue and predicted SRS in the 2017 Pre-NIL model

Revenue (\$100K)	Marginal association ($f'(x)$)	Correlation
(\$1M)	0.79894	At this revenue level, the regression corresponds to ~0.80 additional SRS points per \$100,000
(\$5M)	0.15978	At this revenue level, the regression corresponds to ~ 0.16 additional SRS points per \$100,000
(\$14M)	0.05706	At this revenue level, the regression corresponds to ~ 0.06 additional SRS points per \$100,000

3.1.1 Pre-NIL period equation and graph

The 2017 data demonstrate a positive but nonlinear association between estimated game-day ticket revenue and SRS. Programs at the lower end of the revenue range exhibit substantial variation in performance, including both strongly negative and positive SRS values. As estimated revenue increases, however, the fitted logarithmic curve rises while

progressively flattening, visually demonstrating the diminishing-return relationship described by the regression equation. The greatest predicted gains in SRS therefore occur across the lower portion of the revenue range, whereas equivalent increases in revenue correspond to progressively smaller predicted performance gains among higher-revenue programs.

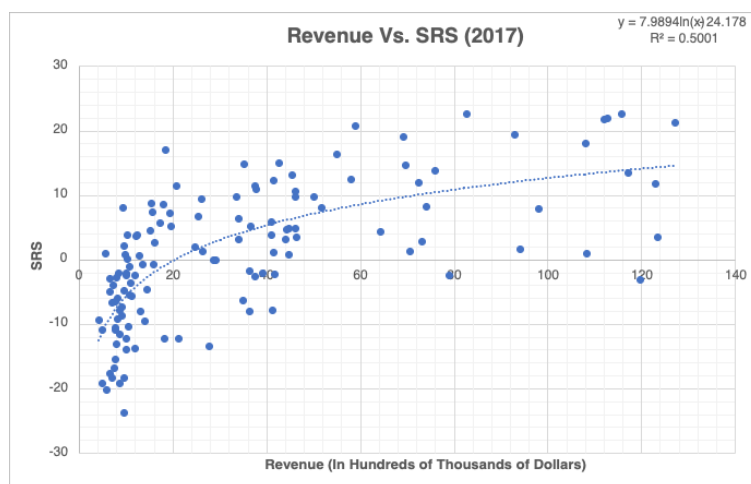


Figure 1. Relationship between estimated game-day ticket revenue and athletic performance in the 2017 pre-NIL period. Each point represents an FBS program, with estimated average game-day ticket revenue expressed in units of \$100,000 and athletic performance measured using the Simple Rating System (SRS). The fitted logarithmic regression, $f(x)=7.9894\ln(x)-24.178$, shows a positive association between estimated revenue and SRS with diminishing returns at higher revenue levels ($R^2=0.5001$).

The distribution of observations around the fitted curve also demonstrates that revenue alone does not determine athletic performance. Programs with similar estimated revenues can exhibit markedly different SRS values, and several observations deviate substantially from the fitted relationship. Nevertheless, the overall upward trajectory of the data is sufficiently pronounced for the logarithmic model to account for ~ 50% of the observed variation in SRS ($R^2=0.5001$). Thus, the pre-NIL results establish two features that provide the baseline for subsequent comparison with 2025: a substantial positive association between estimated financial strength and on-field performance, and diminishing predicted performance returns as revenue increases.

3.1.2 *Pre-NIL period coefficient of determination understanding*

A coefficient of determination of $R^2=0.5001$ indicates that ~ 50% of the observed variation in SRS across FBS programs in 2017 is accounted for by the fitted relationship with estimated game-day ticket revenue. Given that team performance is influenced by numerous factors beyond financial resources, this represents a substantial association for a model containing a single primary financial predictor. The remaining variation may reflect factors not incorporated into the model, including coaching quality, player talent and development, team cohesion, schedule-specific effects, home-field environment, and other program- and season-specific characteristics. Importantly, the R^2 value should not be interpreted as evidence that revenue *causes* 50% of team performance; rather, it indicates the proportion of observed SRS variation accounted for by the fitted revenue–performance relationship. The stability of this relationship and its comparison with the

2025 post-NIL model are examined further in the statistical testing section.

3.1.3 *Pre-NIL period notable outliers*

Despite the overall fit of the 2017 model, several programs deviated substantially from their predicted SRS values, demonstrating that estimated game-day ticket revenue alone does not fully account for variation in on-field performance. UCF represents one of the most notable positive outliers. With ~ \$1.8 million in estimated game-day ticket revenue, UCF fell below the model's estimated break-even revenue level and had a predicted SRS of -0.91 . The team nevertheless completed an undefeated 2017 season and achieved an actual SRS of 16.90, representing a positive deviation of ~ 17.81 SRS points from the model prediction. UCF's season featured a highly productive offense led by quarterback and Heisman Trophy finalist Mackenzie Milton. The program had also undergone a dramatic competitive turnaround following its winless 2015 season. Thus, UCF illustrates the extent to which exceptional team-level circumstances can coincide with performance substantially exceeding that predicted from estimated financial resources alone.

Oklahoma was another prominent positive outlier. The model predicted an SRS of ~ 9.67, whereas Oklahoma achieved an SRS of 19.05, ~ 9.38 points above the predicted value. The team was led by Heisman Trophy-winning quarterback Baker Mayfield and advanced to the College Football Playoff semifinal, where it lost to Georgia in double overtime. In this case, the model correctly predicted above-average performance but substantially underestimated its magnitude.

Large deviations also occurred in the opposite direction. Tennessee and Kansas had predicted SRS values of 14.05 and 0.26, respectively, but recorded actual values of -3.18 and -12.35 . Tennessee therefore underperformed its model prediction by ~ 17.23 SRS points, while Kansas underperformed by ~ 12.61 points. Tennessee's season included an 0–6 start in SEC play and culminated in the dismissal of head coach Butch Jones, while Kansas experienced substantial competitive difficulties despite the financial resources represented by the model.

Collectively, these outliers illustrate an important feature of the 2017 results: estimated financial strength was associated with SRS at the population level but was not determinative of performance at the individual-program level. Exceptional player performance, coaching and tactical differences, roster composition, injuries, program stability, and other unmeasured factors may contribute to substantial departures from the regression prediction. The outliers therefore complement the $R^2=0.5001$ result by showing concretely how a model that accounts for $\sim$ half of the observed variation can nevertheless substantially overpredict or underpredict the performance of particular programs.

3.2 Revenue and performance after NIL (2025)

The fitted regression equation for the 2025 model is, $f(X)=7.5526\ln(X)-22.271$ (eq.4). Among the functional forms evaluated, including linear, exponential, step, and higher-order polynomial models, the logarithmic specification produced the highest coefficient of determination and therefore provided the best fit to the observed 2025 data. As in 2017, the logarithmic form indicates a diminishing marginal relationship between estimated game-day ticket revenue and predicted SRS: as

estimated revenue increases, equivalent additional increments in revenue are associated with progressively smaller increases in predicted SRS. Thus, although higher estimated financial resources remain associated with stronger predicted athletic performance, the magnitude of this association progressively decreases at higher revenue levels.

The post-NIL environment also provides an important context for interpreting the 2025 relationship. NIL has expanded the range of mechanisms through which programs and student-athletes interact financially, while factors such as endorsements, program location, recruiting opportunities, and NIL arrangements may influence recruiting decisions and the allocation of program resources. However, the present revenue variable measures estimated game-day ticket revenue rather than NIL expenditures or athlete compensation. Consequently, the regression cannot determine whether programs redirected financial resources toward NIL opportunities or whether NIL itself altered the manner in which financial resources translated into athletic performance. These possibilities are considered in the Discussion rather than inferred directly from the regression results.

Another informative feature of the 2025 equation is its estimated break-even point. Setting the fitted function equal to zero, $f(X)=0$ and substituting Eq. 4 gives, $7.5526\ln(X)-22.271=0$, which yields $X\approx 19.08$.

Because X represents estimated average game-day ticket revenue in units of \$100,000, this corresponds to $\sim$ \$1.908 million. At this revenue level, the fitted model predicts an SRS of 0, representing $\sim$ average performance within the

FBS comparison. This estimated threshold is slightly lower than the corresponding 2017 value of $\sim \$2.062$ million. However, the difference between these model-derived break-even points should be interpreted descriptively and does not by itself establish a statistically significant change in the revenue–performance relationship between the two periods.

The first derivative of the 2025 fitted function is $f'(X)=X7.5526$ (eq.5). The derivative quantifies the marginal association between estimated revenue and predicted SRS at a given revenue level. Because $f'(X)$ decreases as X increases, equivalent incremental increases in estimated revenue are associated with progressively smaller increases in predicted SRS at higher revenue levels. Representative values of this marginal association are presented in Table 2.

Table 2. Marginal association between estimated game-day ticket revenue and predicted SRS in the 2025 Post-NIL model

Revenue (\$100K)	Marginal association ($f'(x)$)	Correlation
(\$1M)	0.75526	At this revenue level, the regression corresponds to ~ 0.76 additional SRS points per \$100,000
(\$5M)	0.15105	At this revenue level, the regression corresponds to ~ 0.15 additional SRS points per \$100,000
(\$14M)	0.05394	At this revenue level, the regression corresponds to ~ 0.05 additional SRS points per \$100,000

3.2.1 Post-NIL period equation and graph

The 2025 data demonstrate a positive, nonlinear association between estimated game-day ticket revenue and athletic performance following the implementation of NIL. As estimated revenue increases, the fitted logarithmic curve rises but progressively flattens, indicating that higher-revenue programs generally exhibit higher predicted SRS values while the marginal increase in predicted performance becomes smaller at progressively higher revenue levels.

As in the pre-NIL period, considerable variation is evident around the fitted curve. Programs with similar estimated game-day revenues can exhibit substantially different SRS values, demonstrating that financial strength alone does not fully account for differences in athletic performance. Nevertheless, the logarithmic

model accounts for $\sim 55\%$ of the observed variation in SRS across FBS programs in 2025 ($R^2=0.5512$).

The overall shape of the 2025 relationship therefore retains the principal characteristics observed in the pre-NIL model: a positive association between estimated financial resources and performance accompanied by diminishing marginal returns at higher revenue levels. Although the 2025 model has a numerically higher R^2 than the 2017 model, this difference alone does not establish that revenue became a stronger determinant of athletic performance following NIL. Whether the relationship changed significantly between the two periods is evaluated formally in Section 3.3 using the Chow test and bootstrap analysis.

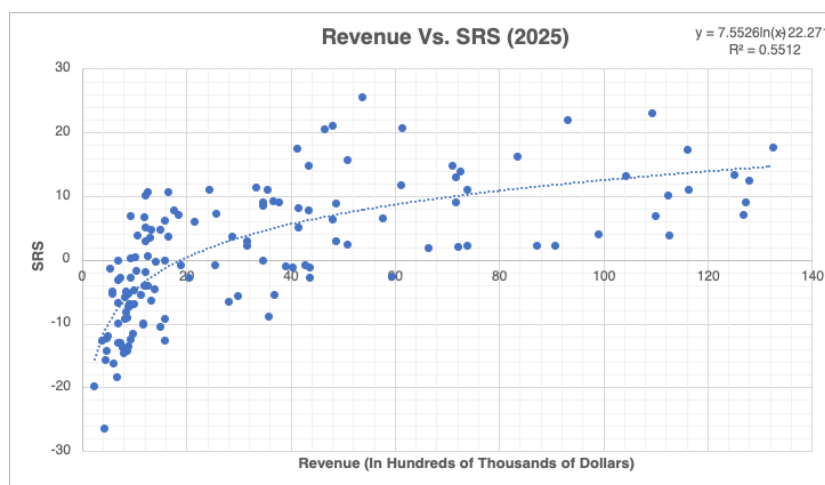


Figure 2. Relationship between estimated game-day ticket revenue and athletic performance in the 2025 post-NIL period. Each point represents an FBS program, with estimated average game-day ticket revenue expressed in units of \$100,000 and athletic performance measured using the Simple Rating System (SRS). The fitted logarithmic regression shows a positive association between estimated revenue and SRS with diminishing marginal returns at higher revenue levels ($R^2=0.5512$).

3.2.2 Post-NIL period coefficient of determination understanding

A coefficient of determination of $R^2=0.5512$ indicates that ~ 55% of the observed variation in SRS across FBS programs in 2025 is accounted for by the fitted relationship with estimated game-day ticket revenue. Although this value is numerically higher than the $R^2=0.5001$ observed for 2017, the difference should not by itself be interpreted as evidence that financial resources became more strongly associated with athletic performance following the introduction of NIL. Whether the revenue–performance relationship changed significantly between the two periods is evaluated formally in the statistical testing section.

The remaining ~ 45% of SRS variation is not accounted for by the 2025 revenue model and may reflect factors not included in the analysis, such as player talent and development,

coaching, team chemistry, injuries, roster composition, and other program- or season-specific influences. Thus, while estimated game-day ticket revenue exhibits a substantial association with athletic performance in 2025, it remains only one component of the broader set of factors associated with competitive outcomes.

3.2.3 Post-NIL period notable outliers

Although the 2025 model accounts for a substantial proportion of the variation in SRS, several programs deviated markedly from their predicted values. Indiana represents one of the most prominent positive outliers, recording an SRS of 25.48 compared with a model-predicted value of ~ 7.82, a positive deviation of ~ 17.66 SRS points. Indiana therefore performed substantially better than would be expected based on estimated game-day ticket revenue alone. Exceptional player performance,

including the contribution of Heisman Trophy winner Fernando Mendoza, represents one possible program-specific factor not captured by the financial model. More broadly, such an outlier demonstrates that resources outside the ticket-revenue proxy, as well as differences in player talent, coaching, roster construction, and resource allocation, may contribute to performance beyond that predicted by the model.

Texas Tech similarly exceeded its predicted performance, achieving an SRS of 21.06 compared with a predicted value of ~ 6.98 , corresponding to a positive deviation of ~ 14.08 SRS points. An additional limitation of the revenue proxy may be particularly relevant for programs with exceptionally high stadium utilization. Texas Tech, BYU, and Oregon recorded attendance corresponding to $\sim 99.89\%$, 102% , and 108% of listed stadium capacity, respectively. Such attendance patterns may not be fully represented by the standardized ticket-price assumptions used to estimate game-day revenue. Consequently, programs with unusually strong ticket demand could generate actual ticket revenues that differ from the model estimates, particularly when ticket prices vary substantially with demand.

Substantial negative outliers were also observed. Florida generated $\sim \$11$ million in estimated game-day ticket revenue and had a predicted SRS of ~ 13.4 , but recorded an actual SRS of only 3.79. South Carolina similarly generated $\sim \$10$ million in estimated revenue but achieved an SRS of 3.92 compared with a predicted value of ~ 12.4 . LSU also performed below its model prediction. These cases demonstrate that high estimated financial resources do not necessarily translate into

correspondingly high athletic performance within an individual season.

Collectively, the positive and negative outliers reinforce an important feature of the 2025 results: the regression describes an overall association between estimated financial strength and athletic performance rather than determining the performance of individual programs. Player performance, coaching, injuries, roster composition, resource allocation, scheduling, and other program-specific factors are not explicitly represented in the model and may contribute to substantial deviations from predicted SRS. The presence of these outliers is therefore consistent with the $\sim 45\%$ of SRS variation not accounted for by the fitted revenue model.

3.3 Statistical comparison of the revenue-performance relationships

3.3.1 Statistical testing: Chow test setup

Figure 3 presents the pooled dataset comprising all 264 team-season observations from 2017 and 2025. Fitting these observations with a single logarithmic regression produces the restricted model, $f(x)=7.7424\ln(x)-23.122$ (eq.6), in which both years are constrained to share the same intercept and slope. The pooled model yielded $R^2=0.5244$, which falls between the values obtained independently for 2017 ($R^2=0.5001$) and 2025 ($R^2=0.5512$). Thus, at the descriptive level, a single fitted relationship retains a degree of explanatory power comparable to that of the two year-specific models. Whether the loss of fit produced by this restriction is statistically significant, however, cannot be determined from the R^2 values alone and is evaluated formally using the Chow test in Section 3.3.2.

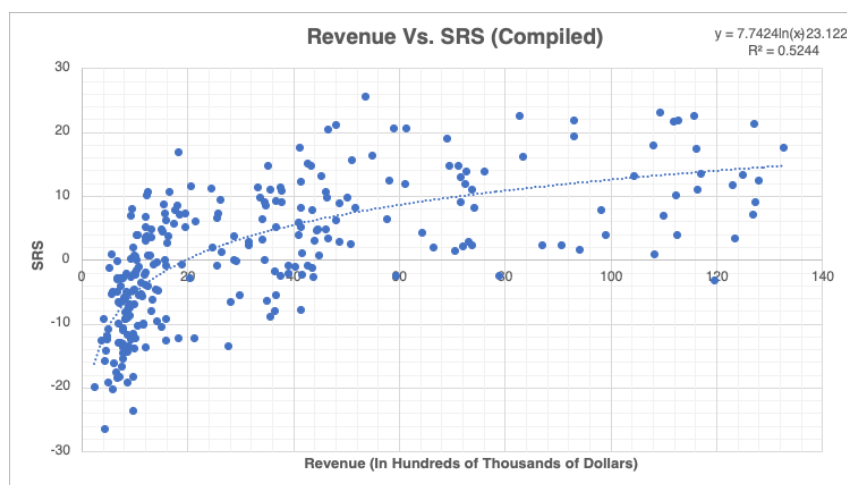


Figure 3. Pooled and year-specific logarithmic relationships between estimated game-day ticket revenue and athletic performance for 2017 and 2025. Each point represents an FBS program in its respective season, with estimated average game-day ticket revenue expressed in units of \$100,000 and athletic performance measured using the Simple Rating System (SRS). The 2017 and 2025 regressions represent the unrestricted models, in which each year is permitted its own intercept and slope, while the pooled regression represents the restricted model, in which observations from both years are constrained to a common relationship. The resulting residual sums of squares were used in the Chow test to determine whether the revenue–performance relationship differed significantly between the pre- and post-NIL periods.

The restricted model contains fewer free parameters than the unrestricted approach. In the pooled model, a single intercept and slope are estimated from all 264 observations, whereas the unrestricted approach permits the 2017 and 2025 datasets to have separate intercepts and slopes. Because the unrestricted models have greater flexibility, their combined residual error cannot exceed that of the corresponding restricted model fitted to the same observations. Accordingly,

$$SSR_{\text{pooled}} \geq SSR_{2017} + SSR_{2025}.$$

For the Chow test, the residual sums of squares from the independently fitted 2017 and 2025 models are therefore combined as $SSR_{2017} + SSR_{2025}$. This produces the unrestricted-model residual error across the same 264 team-season observations represented by SSR_{pooled} , allowing

a like-for-like comparison between the restricted and unrestricted specifications. Importantly, the 264 observations represent team-seasons rather than 264 unique programs, because most programs are represented once in 2017 and again in 2025. The Chow test then evaluates whether the reduction in residual error obtained by allowing separate year-specific relationships is sufficiently large, relative to the additional model parameters and residual variation, to provide evidence of a structural difference between the 2017 and 2025 revenue–performance relationships.

3.3.2 Statistical testing: *F*-statistic and results

The Chow test evaluates whether the increase in residual error produced by imposing a common regression relationship is greater than would be expected from sampling variation, or if it is

small enough that a single shared regression line could reasonably explain both years' data. This can be quantified using the F-statistic,

$$F = \frac{\frac{SSR_{pooled} - (SSR_{unrestricted})}{k}}{\frac{SSR_{unrestricted}}{n - 2k}} \quad (\text{eq.7}), \text{ where}$$

$SS R_{unrestricted} = SS R_{2017} + SS R_{2025}$, $k=2$ (shared intercept and slope), and $n=264$ (total number of team-seasons across 2017 and 2025).

To determine all three SSR values, Residuals and the corresponding sums of squared residuals were calculated using Python, ultimately determining each residual value, squaring it, and then summing them all together, which resulted in $SS R_{pooled} = 13242.91$ and $SS R_{unrestricted} = 13211.98$. Substitution of the corresponding SSR values into the Chow-test equation yielded $F=0.304$. With the appropriate degrees of freedom, this corresponded to $p=0.738$, indicating that the null hypothesis of a common revenue–performance relationship across the two periods could not be rejected.

3.3.3 Statistical testing: bootstrap implementation and validation

The bootstrap analysis produced a 95% confidence interval of $[-0.094, 0.197]$ for the difference in the coefficient of determination. The observed difference between the 2025 and 2017 models, $[0.5512 - 0.5001 = 0.0511]$, fell well within this interval. Similarly, the 95% confidence interval for the difference in slope coefficients was $[-2.17, 1.40]$, which contained the observed slope difference of $[7.5526 - 7.9894 = -0.4368]$. Because both confidence intervals included zero and contained the observed cross-period differences, the bootstrap analysis provided no evidence that

either R^2 or the slope coefficient differed significantly between 2017 and 2025. Consistent with the Chow-test results, these findings indicate that the available data do not support a statistically detectable change in the fitted revenue–performance relationship between the pre- and post-NIL periods.

3.4 Recruiting concentration before and after NIL

3.4.1 Recruiting concentration: Gini coefficient results

The Gini analysis identified a decrease in the concentration of recruiting-point totals across FBS programs between the pre- and post-NIL periods. Using the program-level recruiting-point data described in Section 2.6, the Gini coefficient was 0.1767 in 2017 and 0.1451 in 2025, corresponding to an absolute change of $[0.1451 - 0.1767 = -0.0315]$.

Because lower Gini coefficients indicate a more even distribution, the decrease from 0.1767 to 0.1451 indicates that recruiting-point totals were less concentrated across FBS programs in 2025 than in 2017. Expressed relative to the 2017 value, this represents an $\sim 17.8\%$ reduction in the Gini coefficient. Thus, the post-NIL sample exhibited a measurably more even distribution of aggregate recruiting-point totals across programs. The recruiting data used to calculate these coefficients were obtained from the respective 2017 and 2025 recruiting datasets (5,6).

Importantly, the magnitude and direction of the observed difference alone do not establish whether the change exceeds that expected from sampling variability. The bootstrap procedure described in Section 2.6 was therefore used to

quantify uncertainty in the difference between the two Gini coefficients. Across 5,000 bootstrap iterations, the 95% confidence interval for the 2025-minus-2017 Gini difference was $[-0.057, -0.005]$. Because the entire interval lies below zero, the analysis indicates that the reduction in recruiting-point concentration was statistically distinguishable from zero under the bootstrap procedure.

This finding differs from the revenue–performance comparison reported in Section 3.3. Whereas the Chow test and bootstrap analysis provided no evidence of a statistically detectable change in the revenue–SRS relationship between 2017 and 2025, the recruiting analysis identified a statistically detectable decrease in the concentration of recruiting-point totals. The two analyses therefore capture different dimensions of competitive balance: the relationship between estimated financial strength and on-field performance remained statistically stable, while the distribution of recruiting-point totals became more even across programs.

The Gini result should not, however, be interpreted as demonstrating that individual elite recruits became more evenly distributed or that NIL caused the observed redistribution. The analysis measures inequality in aggregate program recruiting-point totals, not the destinations or movements of individual recruits. Accordingly, the result establishes that program-level recruiting scores were less concentrated in the 2025 sample; possible

mechanisms underlying this change are considered in the Discussion.

3.4.2 *Competitive balance in recruiting: Lorenz curve and interpretation*

The Lorenz curves provide a visual representation of the change in recruiting-point concentration identified by the Gini analysis. As shown in Figure 4, the 2025 curve lies consistently closer to the line of perfect equality than the 2017 curve, indicating that aggregate recruiting-point totals were distributed more evenly across FBS programs in 2025. This pattern is consistent with the reduction in the Gini coefficient from 0.1767 in 2017 to 0.1451 in 2025. Moreover, the bootstrap 95% confidence interval for the difference, $[-0.057, -0.005]$, excludes zero, indicating that the observed reduction in recruiting-point concentration was statistically distinguishable from zero under the resampling procedure.

This result provides an important contrast with the revenue–performance analysis. The relationship between estimated game-day ticket revenue and SRS did not differ significantly between 2017 and 2025, whereas the distribution of recruiting-point totals became significantly more even across FBS programs. Taken together, the results therefore do not support a simple post-NIL pattern in which financial advantage became increasingly concentrated among already dominant programs. Instead, they reveal stability in the aggregate revenue–performance relationship alongside a measurable decrease in recruiting-point concentration.

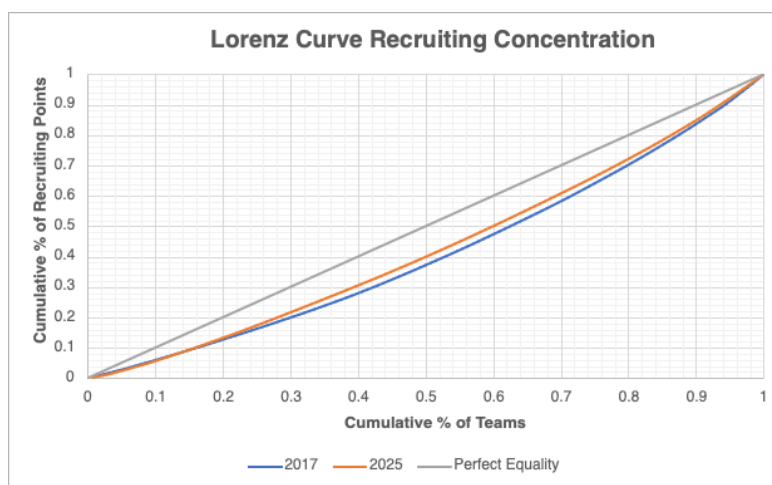


Figure 4. Lorenz curves of recruiting-point distributions across FBS programs in 2017 and 2025. The curves show the cumulative proportion of total recruiting points accounted for by the cumulative proportion of FBS programs, ordered from lowest to highest recruiting-point total. The diagonal represents perfect equality, in which recruiting points would be distributed equally across programs. The 2025 Lorenz curve lies closer to the line of equality than the 2017 curve, consistent with the lower Gini coefficient observed in 2025 (0.1451) compared with 2017 (0.1767), indicating a more even distribution of aggregate recruiting-point totals across FBS programs in the post-NIL sample.

The recruiting result should nevertheless be interpreted within the scope of the metric used.

The Gini coefficient measures the distribution of aggregate program recruiting-point totals and does not identify the destinations of individual recruits, the distribution of the highest-rated recruits specifically, or the mechanisms responsible for the observed change. Consequently, the present analysis cannot determine whether NIL itself produced the redistribution or whether it arose from other changes in the collegiate football environment between 2017 and 2025. Potential explanations for this pattern, its implications for competitive balance, and the distinction between recruiting-point concentration and individual elite-recruit movement are considered in the Discussion.

4. Discussion

4.1 Stability of the revenue–performance relationship

One of the clearest features of both the 2017 and 2025 models is the logarithmic relationship between estimated game-day ticket revenue and Simple Rating System (SRS) performance. In both periods, higher estimated revenue was associated with stronger predicted performance, but the magnitude of this association decreased progressively at higher revenue levels. This diminishing-return pattern is reflected mathematically in the derivatives of the fitted models. In 2017, the estimated marginal gain declined from ~ 0.80 SRS points per additional \$100,000 at a revenue level of \$1 million to ~ 0.06 points at \$14 million. The corresponding values in 2025 were ~ 0.76 and 0.05 SRS points, respectively. Thus, the models suggest that differences in financial resources are associated with substantially larger predicted performance

differences among lower-revenue programs than among programs already operating at high estimated revenue levels.

Importantly, the higher coefficient of determination observed in 2025 should not be interpreted as evidence that financial resources became more important after the introduction of NIL. The R^2 increased from 0.5001 in 2017 to 0.5512 in 2025, meaning that the fitted model accounted for a somewhat larger proportion of the observed variation in SRS in the 2025 sample. However, a difference between two sample R^2 values does not by itself demonstrate that the underlying revenue–performance relationship changed. The formal statistical analyses performed in this study provide no evidence for such a structural shift. The Chow test yielded $F = 0.304$ and $p = 0.738$, indicating that allowing separate regression relationships for 2017 and 2025 did not significantly improve model fit relative to a shared relationship. Similarly, bootstrap analysis showed that the observed R^2 difference of 0.0511 fell within the 95% confidence interval for plausible cross-period differences $[-0.094, 0.197]$. The observed slope difference of -0.4368 likewise fell within its bootstrap interval $[-2.17, 1.40]$. Consequently, the apparent increase in R^2 is consistent with sampling variation rather than evidence that money became a stronger determinant of performance in the post-NIL period.

The similarity of the fitted relationships reinforces this interpretation. The logarithmic coefficient decreased only modestly, from 7.9894 in 2017 to 7.5526 in 2025, while the estimated revenue associated with an SRS of zero shifted from $\sim \$2.062$ million to $\$1.908$ million. Although these numerical differences

are descriptively interesting, they should not be treated as evidence of a substantive NIL-associated restructuring because the statistical comparison does not support separation of the two regression relationships. The more defensible interpretation is therefore one of stability rather than strengthening: within the two periods examined, financial strength remained meaningfully associated with on-field performance and continued to exhibit diminishing returns, but there is no statistical evidence that this relationship became stronger following the introduction of NIL.

This result is important because it separates the continued importance of financial resources from the question of whether NIL intensified that importance. The analysis supports the former but not the latter. Higher-resource programs remained advantaged in predicted SRS, yet the diminishing-return structure indicates that additional estimated revenue was associated with progressively smaller performance differences at the upper end of the financial distribution. More importantly, the post-NIL data do not demonstrate a new or steeper financial gradient in athletic performance. The principal change identified elsewhere in this study therefore lies not in a strengthened revenue–performance relationship, but in the distribution of recruiting-point totals across programs.

4.2 Redistribution of recruiting strength in the NIL era

In contrast to the stability of the revenue–performance relationship, the recruiting analysis identified a statistically significant difference between the pre- and post-NIL periods. The Gini coefficient for recruiting-point totals decreased from 0.1767 in 2017 to 0.1451 in 2025,

corresponding to a difference of -0.0315 . Importantly, the bootstrapped 95% confidence interval for this difference $[-0.057, -0.005]$ excluded zero, indicating that the observed reduction in recruiting-point concentration was unlikely to be explained by sampling variation alone. The Lorenz curves provide a complementary visualization of this result, with the 2025 distribution lying closer to the line of equality than the 2017 distribution. Together, these analyses indicate that recruiting-point totals were significantly more evenly distributed across FBS programs in 2025 than in 2017.

This finding is particularly informative because it identifies a measurable change in competitive balance that was not apparent from the revenue–performance analysis. The result does not mean that all programs recruited equally in 2025 or that traditional recruiting advantages disappeared. Rather, it indicates that recruiting-point totals were less concentrated among a relatively small portion of FBS programs. In statistical terms, the distribution broadened across programs even though substantial differences in recruiting strength remained. Competitive balance in recruiting should therefore be viewed as a continuum rather than as a binary distinction between concentration and equality.

The timing of this redistribution is consistent with NIL having contributed to a changing recruiting environment, but the present analysis cannot establish NIL as its cause. NIL potentially expands the set of benefits available to recruits beyond traditional measures of program prestige and institutional resources, allowing different programs to compete through varying combinations of financial opportunity and other program characteristics. However, the

study does not measure individual NIL offers, athlete compensation, recruit decision-making, or the reasons athletes selected particular institutions. Conference realignment, transfer activity, changes in recruiting strategies, and other developments between 2017 and 2025 could also have contributed to the observed distribution. The statistically supported conclusion is therefore narrower: recruiting-point totals were significantly more evenly distributed across FBS programs in the post-NIL comparison year, and this change occurred during the broader transformation of college football associated with the NIL era.

An additional distinction concerns what the Gini coefficient actually measures. The analysis evaluates each program's aggregate recruiting-point total rather than the distribution of individual recruits according to star rating or national ranking. A lower Gini coefficient therefore does not demonstrate that the highest-rated recruits became less concentrated among elite programs. It is possible, for example, for overall recruiting-point totals to become more evenly distributed while the highest-ranked subset of recruits remains concentrated. Determining whether NIL altered the distribution of elite talent specifically would require recruit-level analysis and represents a separate question from the program-level distribution examined here.

Nevertheless, the significant reduction in recruiting-point concentration provides an important counterpoint to the stability observed in the financial-performance models. Whereas the study found no statistically detectable restructuring of the relationship between estimated revenue and SRS, it did identify a measurable redistribution in an important

competitive input. This suggests that assessments of competitive balance in the NIL era should not rely exclusively on wins, ratings, or financial-performance relationships. Changes may first become detectable in how competitive resources such as recruiting strength are distributed across programs, even when corresponding differences in realized on-field performance are not yet evident.

4.3 Recruiting redistribution without performance restructuring

Taken together, the revenue–performance and recruiting analyses reveal the central finding of this study: competitive balance changed measurably in recruiting-point distribution without a corresponding detectable restructuring of the relationship between financial strength and on-field performance. The Gini analysis showed that recruiting-point totals were significantly more evenly distributed across FBS programs in 2025 than in 2017, whereas the Chow test and bootstrap analyses found no statistically significant difference between the revenue–SRS relationships across the same periods. These results demonstrate that different dimensions of competitive balance need not change simultaneously.

This distinction is important because recruiting strength represents an input into competitive performance rather than performance itself. A broader distribution of recruiting points does not necessarily produce an immediate corresponding redistribution of SRS, wins, or other on-field outcomes. Recruited players must first enter and remain within programs, develop within their respective systems, and contribute to team performance. Their eventual impact also occurs alongside numerous factors not captured by the present model, including coaching,

injuries, roster continuity, player development, scheduling, and team chemistry. Consequently, even a genuine change in recruiting distribution could coexist with an apparently stable performance structure, particularly when comparing only two seasons.

The findings therefore suggest a useful distinction between upstream competitive redistribution and downstream competitive outcomes. Recruiting-point totals provide evidence concerning how one important competitive resource is distributed among programs, whereas SRS reflects the realized performance that emerges after recruiting strength interacts with financial and nonfinancial factors. In the present analysis, the upstream measure changed significantly while the downstream relationship between estimated financial resources and performance did not. This separation would be obscured if competitive balance were evaluated using either recruiting or on-field performance alone.

The result also changes how the effect of NIL should be interpreted. The data do not support the stronger claim that NIL has already “leveled the playing field” in FBS football. The continued association between estimated revenue and SRS indicates that financial differences remain relevant to performance, and the similarity of the 2017 and 2025 regression relationships provides no evidence that this financial gradient has disappeared. Conversely, the results also do not support the simple expectation that the NIL era has necessarily intensified financial dominance on the field. If that had occurred strongly within the variables examined here, a substantial restructuring of the revenue–performance relationship might have

been expected; no such statistically detectable change was observed.

Instead, the results identify a more specific pattern: the post-NIL comparison year was characterized by less concentrated recruiting-point totals alongside a statistically stable revenue–performance relationship. This raises the possibility that structural changes in college football may become detectable at different stages of the pathway connecting financial resources, talent acquisition, and athletic performance. However, the present two-period design cannot determine whether the recruiting redistribution preceded NIL, resulted from NIL, or will eventually translate into greater parity in on-field outcomes. Establishing such a progression would require longitudinal analysis across multiple pre- and post-NIL seasons.

This distinction provides a potentially useful framework for future evaluation of the NIL era. Rather than asking only whether college football has become more or less competitive, future studies can examine separately whether NIL-era changes are occurring in the acquisition and distribution of competitive resources and whether those changes subsequently propagate into realized competitive outcomes. Recruitment-level rankings, transfer-portal movement, roster retention, direct NIL expenditures, and multi-season performance measures could help determine whether the redistribution observed here persists and whether it ultimately alters on-field competitive balance. The present findings establish the first part of that pathway within the variables examined: recruiting-point distribution differed significantly between 2017 and 2025, while the financial relationship with realized performance remained statistically indistinguishable.

5. Limitations

Several limitations should be considered when interpreting the findings of this study. Most importantly, the analysis compares two proxy seasons, 2017 and 2025, rather than longitudinal panels spanning multiple years before and after the introduction of NIL. The two-year design was selected to avoid the disruptions surrounding the COVID-19 pandemic and the transitional period surrounding NIL implementation while maintaining temporal symmetry around 2021. Nevertheless, two observations in time cannot establish a longitudinal trend or isolate NIL from other changes occurring in college football between 2017 and 2025. Accordingly, the observed differences between the two periods should be interpreted as cross-period associations rather than causal effects of NIL.

The financial variable also represents an estimate of game-day ticket revenue rather than total program revenue or NIL resources. Ticket prices were ~ using conference-level tiers, meaning that schools within the same conference were generally assigned the same average ticket price despite potentially substantial differences in stadium demand, program prestige, and actual ticket pricing. In addition, changes in ticket prices between 2017 and 2025 were not modeled directly. These approximations introduce uncertainty into the absolute revenue estimates, although the study primarily uses them as a standardized proxy for comparing financial strength across programs.

More broadly, ticket revenue captures only one component of the financial resources available to an FBS football program. Donor contributions, media and advertising agreements, sponsorships, merchandise,

concessions, parking, institutional support, and other revenue streams were not incorporated. Most importantly for the interpretation of the post-NIL period, the analysis does not measure NIL compensation or NIL-related expenditures directly. Estimated ticket revenue should therefore not be interpreted as a direct measure of the amount of NIL funding available to athletes or programs.

SRS likewise provides a standardized but incomplete representation of athletic performance. Although it incorporates point differential and strength of schedule, it cannot capture many factors that influence team outcomes, including injuries, coaching changes, player development, roster continuity, team chemistry, and other season-specific effects. These unmeasured factors likely contribute to the substantial variation around the fitted revenue–SRS relationships and limit the extent to which financial variables alone can explain on-field performance.

Cross-period comparisons are further complicated by changes in the composition and organization of FBS football. Several programs changed conferences between 2017 and 2025, while other programs entered the FBS during the intervening period. Conference realignment can alter schedules, competitive strength, attendance, recruiting environments, and the financial context in which programs operate. The 2017 and 2025 attendance data were also obtained from different sources, creating the possibility of minor differences in reporting or data-collection methodology between periods.

The recruiting analysis has additional limitations. Recruiting-point totals are aggregate measures produced using an

externally defined scoring methodology and are less transparent than analyses based on individual recruit ratings. A program's total recruiting points may also reflect roster-building decisions extending beyond a single season. Consequently, the statistically significant decline in the Gini coefficient demonstrates that aggregate recruiting-point totals were more evenly distributed across FBS programs in 2025 than in 2017, but it does not establish that elite recruits themselves became more evenly distributed, identify which categories of recruits changed programs, or demonstrate that NIL caused individual recruiting decisions.

This distinction is particularly important because the study identifies different patterns for recruiting distribution and on-field performance. The observed reduction in recruiting-point concentration should not be interpreted as evidence that NIL has already produced greater parity in athletic outcomes. Likewise, the absence of a statistically detectable change in the revenue–SRS relationship does not establish that NIL has had no effect on competitive balance. Rather, the available data support the narrower conclusion that recruiting-point totals were significantly more evenly distributed in the post-NIL comparison year, while the estimated relationship between financial strength and on-field performance was not statistically distinguishable between the two periods.

Future studies could address these limitations by incorporating multiple pre- and post-NIL seasons, school-specific revenue and ticket-price data, direct estimates of NIL expenditures, transfer-portal activity, individual recruit rankings, roster retention, and additional measures of competitive performance. Such

longitudinal data would also permit stronger statistical designs capable of distinguishing NIL-associated changes from broader temporal changes in collegiate football.

6. Conclusion

This study examined whether the introduction of name, image, and likeness (NIL) compensation coincided with measurable changes in competitive structure within NCAA Division I FBS football by comparing financial strength, on-field performance, and recruiting-point distributions between 2017 and 2025. Taken together, the analyses reveal a more nuanced pattern than the simple expectation that NIL either strengthened the influence of money or immediately “leveled the playing field.”

First, the relationship between estimated game-day ticket revenue and on-field performance remained remarkably stable across the two periods. Revenue exhibited a logarithmic relationship with the Simple Rating System (SRS) performance in both 2017 and 2025, consistent with diminishing marginal returns: increases in estimated revenue were associated with progressively smaller gains in predicted performance. Although R^2 increased from 0.5001 in 2017 to 0.5512 in 2025 and the fitted regression parameters changed modestly, these differences were not statistically distinguishable. The Chow test failed to reject a common revenue–performance relationship ($F = 0.304$, $p = 0.738$), and bootstrap confidence intervals likewise encompassed the observed differences in R^2 and slope. Therefore, within the two periods examined, there is no statistical evidence that NIL fundamentally altered the relationship between estimated financial strength and on-field performance.

The clearest measurable change instead occurred in recruiting distribution. The Gini coefficient for recruiting-point totals declined from 0.1767 in 2017 to 0.1451 in 2025, with the bootstrapped 95% confidence interval for the difference $[-0.057, -0.005]$ excluding zero. Recruiting-point totals were therefore significantly more evenly distributed across FBS programs in 2025 than in 2017. Importantly, this result describes the distribution of total recruiting points across programs; it does not establish that elite recruits themselves became more evenly distributed or that NIL caused individual recruits to select different programs.

The combination of these findings provides the principal insight of this study. A measurable redistribution of recruiting value can occur without a corresponding detectable change in the relationship between financial strength and realized athletic performance. In this sense, recruiting distribution and competitive performance should not be treated as interchangeable measures of competitive balance. The post-NIL landscape examined here shows evidence of change in an upstream competitive input—recruiting-point distribution—while the downstream revenue–performance relationship remains statistically similar to that observed before NIL.

This distinction also suggests a possible temporal interpretation. Changes in recruiting distribution need not immediately translate into changes in wins, losses, or SRS because athletic performance depends on numerous intermediate factors, including player development, coaching, roster retention, injuries, scheduling, and team chemistry. Consequently, the absence of a detectable change in the revenue–

performance relationship does not negate the observed redistribution of recruiting points. Rather, the two results indicate that structural changes within collegiate athletics may emerge at different stages of the pathway from financial resources to talent acquisition and ultimately to on-field performance.

The results therefore provide neither evidence that NIL has fully democratized college football nor evidence that financially dominant programs have simply strengthened their competitive position. Instead, they identify a more specific pattern: the distribution of recruiting-point totals broadened significantly while the financial gradient of on-field performance remained statistically stable. Whether this redistribution eventually produces greater parity in athletic outcomes cannot be determined from the two proxy years analyzed here and represents an important question for longitudinal study. Future analyses incorporating multiple pre- and post-NIL seasons, direct NIL expenditures, transfer-portal activity, individual recruit rankings, roster

retention, and broader measures of athletic-department revenue could determine whether the recruiting redistribution identified here persists and whether it ultimately propagates into measurable changes in competitive performance.

Accordingly, the principal contribution of this study is not a claim that NIL has already leveled the FBS playing field. Rather, it demonstrates that competitive balance can change along one dimension while remaining stable along another. In the period examined, NIL-era college football was characterized by significantly less concentrated recruiting-point totals without a statistically detectable restructuring of the relationship between estimated financial strength and on-field success. This separation between recruiting redistribution and performance stability provides a testable framework for evaluating how the continuing transformation of collegiate athlete compensation may reshape competitive balance over time.

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