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Fan Behavior, Team Success, and Stadium Demand: A Behavioral Economics Perspective from the NFL

Yu Pang[1*], **Fengchen Wang**[1,2]

[1]School of Economy and Management, National Research University Higher School of Economics, St Petersburg 194100, Russia
[2]SmartEdTech Program, Université Côte d'Azur, Nice 06100, France

***Correspondence to:**Yu Pang, National Research University Higher School of Economics, 3A-1, Kantemirovskaya Street, Saint Petersburg 194100, Russia; Email: yupang@hse.ru

Abstract: This study investigates how team performance influences stadium attendance in the National Football League, using a 28-year panel dataset comprising 7,221 games from 37 teams. Employing fixed effects regression models, the analysis examines short-, medium-, and long-term performance indicators-including current season win percentage, historical playoff participation, and lifetime win rates-while accounting for stadium, economic, geographic, and match-level variables. The findings reveal that team performance significantly affects attendance, but its impact varies across the season. While early-season success has little effect, performance becomes increasingly predictive of attendance toward the end of the regular season and during the playoffs. Surprisingly, winning the Super Bowl in the previous season is associated with a decline in attendance the following year, suggesting a possible expectation saturation effect. Long-term team success enhances attendance, particularly in the early season. Additionally, outcome uncertainty, new stadiums, geographic proximity, and per capita income positively influence turnout, while rising unemployment is paradoxically linked to higher attendance. These insights carry implications for sports economists and practitioners, particularly in emerging markets. The methodology and behavioral patterns identified here may inform attendance strategies in professional leagues across Central and Eastern Europe, where fan behavior and infrastructure investments increasingly resemble those of mature sports markets.

Keywords: Sports attendance; Fan behavior; Team performance; Econometric modeling

1. Introduction

Stadium attendance is a central component of financial sustainability in professional sports[1]. Beyond reflecting fan loyalty, it drives revenue through ticket sales, concessions, merchandise, and sponsorships[2]. In the National Football League (NFL), consistent fan turnout is essential to the league's business model, making attendance patterns a key concern for team owners and sports economists alike[3].

Numerous studies have shown that team performance strongly correlates with stadium attendance, regardless of the metric used[4–8]. Pre-game winning percentage is one of the most commonly employed indicators, while other measures such as team rankings, scoring statistics, and goals allowed also demonstrate predictive value[9–11]. Longitudinal performance metrics have also been linked to attendance, particularly in machine learning models that integrate multi-season trends[6, 12]. However, most of these approaches treat performance as a static factor, overlooking temporal variations in fan behavior.

Existing research rarely differentiates how performance at different stages of a season impacts attendance. Early in the season, when outcomes feel less urgent, fans may rely more on team reputation or prior-season memories. In contrast, late-season matches carry more weight, and recent performance becomes a stronger driver of attendance. These shifts suggest that fan behavior is temporally dynamic and warrants closer analysis.

To address this gap, we apply pooled OLS, fixed effects, and random effects models to analyze team performance and attendance across 7,221 NFL games. By introducing stage-specific dummy variables (early, mid-, and late season), we examine how the impact of performance shifts over time. This approach offers a more nuanced view of fan engagement dynamics and provides actionable insights for sports marketers and league managers.

The remainder of this paper is organized as follows: Section 1 describes the econometric model and data; Section 2 presents the empirical findings; Section 3 discusses implications for sports management.

2. Model and Data

This section presents the empirical model, outlines the core performance and control variables, and describes the data sources and sample used in the analysis.

2.1 Model Specification and Theoretical Justification

Our study employs a three-dimensional, panel data econometric model that captures the complexities of attendance dynamics at individual NFL games across 28 seasons. This model allows us to effectively control for various effects and account for heterogeneity inherent in the data[8, 11]. We specify the following regression model to estimate attendance dynamics:

$$Attendance_{ijt} = \beta X_{ijt} + \lambda Z_{ijt} + \alpha_{ij} + \xi_t + \varepsilon_{ijt},\ i = 1,2, \ldots, N,\ j \neq i,\ t = 1, 2, \ldots, T \tag{2.1}$$

where i, j, and t represent indices for the home teams, visiting teams, and weeks in NFL season, respectively. Attendance is the dependent variable representing the number of spectators at each match, β is a parameter vector estimated across the explanatory variables X, which are associated with the performance metrics of the home team. and λ maps the influence of control variables Z.

α_{ij} captures the bilateral effects between home and visiting teams, reflecting the unique interactions that might influence attendance, such as historical rivalries or geographical proximity. Time effect ξ_t accounts for time-specific effects such as macroeconomic conditions or league-wide changes affecting all games in a particular week. ε_{ijt} denotes the stochastic error term, representing unobserved factors specific to each game.

This three-dimensional model extends conventional panel data approaches by explicitly accounting for bilateral interactions between teams. Such interactions are central to sports economics, where matchups—especially those involving rivalries—can substantially influence attendance. By modeling these dynamics, we obtain more accurate estimates of the key performance effects.

2.2 Performance Metrics

To comprehensively capture the influence of team performance on stadium attendance, we construct a multi-dimensional framework consisting of five key indicators. These metrics represent distinct temporal horizons—short-term, medium-term, and long-term success—as well as recent season-specific outcomes.

Short-term performance is proxied by each team's cumulative winning percentage in the current season, calculated prior to each game. This measure reflects recent on-field success and is commonly used in sports economics literature as an indicator of team momentum[5, 7].

Medium-term performance is captured by the number of playoff appearances over the past ten seasons. This variable serves as a measure of sustained competitiveness and historical relevance, factors which may influence fan loyalty and attendance expectations[13].

Long-term performance is represented by the franchise's all-time winning percentage, which is updated on a game-by-game basis. This metric reflects the overall historical strength of the team and acts as a proxy for brand prestige and legacy since the unification of the NFL in 1970.

Additionally, we include two binary indicators to reflect recent team milestones: (1) whether the team qualified for the playoffs in the prior season, and (2) whether the team was the most recent Super Bowl. These variables capture recent success narratives that may shape fan sentiment and pre-season excitement.

2.3 Control Variables

To isolate the impact of team performance on stadium attendance, we control for several factors that may confound this relationship. These controls are grouped into four main categories: game outcome uncertainty, stadium characteristics, geographic and demographic factors, and economic conditions.

2.3.1 Game Outcomes Uncertainty

We incorporate two key betting-related variables obtained from Vegas odds:

(1) Spread: the expected point difference between teams, reflecting perceived dominance;

(2) Over/Under Line: the projected total points scored in a game, indicating anticipated game excitement.

Both metrics influence fan expectations and perceived match quality[14]. To capture nonlinear effects, we also include the square of the spread ($Spread^2$), accounting for threshold effects in fan behavior[8].

2.3.2 Stadium Characteristics

Stadium factors can significantly shape attendance. We include:

(1) A dummy for new stadiums in their inaugural operational year (honeymoon effect);

(2) Stadium age, reflecting aging infrastructure, which may reduce appeal but also carry historical or emotional value[8, 9].

These variables capture both novelty and nostalgia-based influences on fan turnout.

2.3.3 Geographic and Demographic Factors

We control for spatial and demographic influences by including:

(1) Distance between home and visiting team cities, serving as a proxy for travel feasibility and regional rivalry;

(2) Team age, representing the historical presence of a franchise, which may affect loyalty and community ties[15].

2.3.4 Economic Conditions

Economic variables reflect fans' ability to afford attending games. We include:

(1) Real per capita personal income (CPI-adjusted), as a proxy for discretionary spending capacity;

(2) Unemployment rate, capturing economic stress that may affect entertainment spending[1].

All economic indicators are state-level, monthly, and seasonally adjusted.

By incorporating these controls, we aim to ensure that the observed effects of performance on attendance are not confounded by external factors, and that our estimates reflect the true behavioral responses of fans.

2.4 Data Source and Sample Description

This study uses panel data from the Pro Football Reference database, covering all regular-season games in the National Football League (NFL) from the 1992 to 2019 seasons. The dataset includes 7,221 observations corresponding to home games across 37 teams[1]. The sample excludes games held at neutral venues (e.g., the Super Bowl or international games), ensuring consistency in measuring home team attendance.

The dataset is structured as an unbalanced panel, reflecting changes in league composition, team relocations, and new franchise introductions during the study period. For example, the Houston Texans joined the league in 2002, while teams such as the Rams and Raiders relocated during the sample window. For each game, the dataset includes variables on attendance, team performance metrics, betting market indicators (spread and over/under), stadium characteristics, geographic data, and state-level economic indicators (monthly real per capita income and unemployment rate).

Attendance is measured as the total number of spectators present at each home game. All economic variables are adjusted for inflation and seasonality. Variables are described in detail in the preceding sections, and summary statistics are reported in Table 1.

[1] It is important to note that during the period under study, some teams relocated to new cities. These relocations, even when the nearest city is a two-hour drive away, have led us to classify each relocated franchise as a new team entry in the NFL. However, franchises that merely changed their team names, without changing their location, are considered as continuous entities for the purposes of this analysis.

Table 1 Descriptive statistics for all variables (1992–2019).

Variables	Mean	Std.Dev.	Min	Max
Weekly attendance	65691.08	10106.52	15131.00	105121.00
Team Winning Percentage	0.47	0.29	0.00	1.00
Previous Season Playoff	0.39	0.49	0.00	1.00
Previous Season Super Bowl Winner	0.03	0.18	0.00	1.00
Playoff Appearances (10 Years)	3.72	2.34	0.00	10.00
Lifetime Winning Percentage	0.49	0.08	0.00	1.00
Spread	-5.48	3.49	-26.50	0.00
Over/Under Line	42.49	4.89	28.00	63.50
Stadium Age	22.59	19.01	0.00	96.00
New Stadium	0.06	0.24	0.00	1.00
Distance (km)	1606.37	1069.25	8.53	4395.68
Team Age	42.55	24.78	0.00	99.00
Real Per Capita Income (USD)	206.62	38.91	139.85	416.43
Unemployment Rate (%)	5.40	1.93	2.00	16.80

Note. Descriptive statistics are based on 7,221 game-level observations from 1992–2019. Income figures are expressed in thousands of real USD (CPI-adjusted). All binary variables are coded as 0/1.

Descriptive statistics for the key variables used in the analysis are presented in Table 1. The sample includes 7,221 observations from regular-season NFL games between 1992 and 2019. The dependent variable, weekly stadium attendance, ranges from 15,131 to 105,121 spectators, with a mean of approximately 65,691, reflecting substantial variation in fan turnout across games and teams. Team performance metrics show moderate dispersion: the average winning percentage is 0.47, while teams participated in an average of 3.7 playoffs over the past decade. Approximately 39% of teams qualified for the previous season's playoffs, and only 3% entered as reigning Super Bowl champions.

Game outcome uncertainty is represented by the Vegas spread (mean: –5.48) and over/under line (mean: 42.49). The negative spread reflects the typical home-team favoritism. Stadium characteristics vary significantly: stadium age ranges from newly constructed to 96 years old, with an average of 22.6 years. Only 6% of games took place in stadiums during their first operational season. Geographic and demographic indicators show wide dispersion in distance between teams (mean: 1,606 km) and team age (mean: 42.6 years). Finally, economic conditions reveal a mean per capita income of $206.62 and a mean unemployment rate of 5.4%, reflecting the socioeconomic backdrop of fan decision-making.

2.5 Multicollinearity Diagnostics

Prior to estimating the regression models, we conduct a pairwise correlation analysis to assess potential multicollinearity among the explanatory variables.

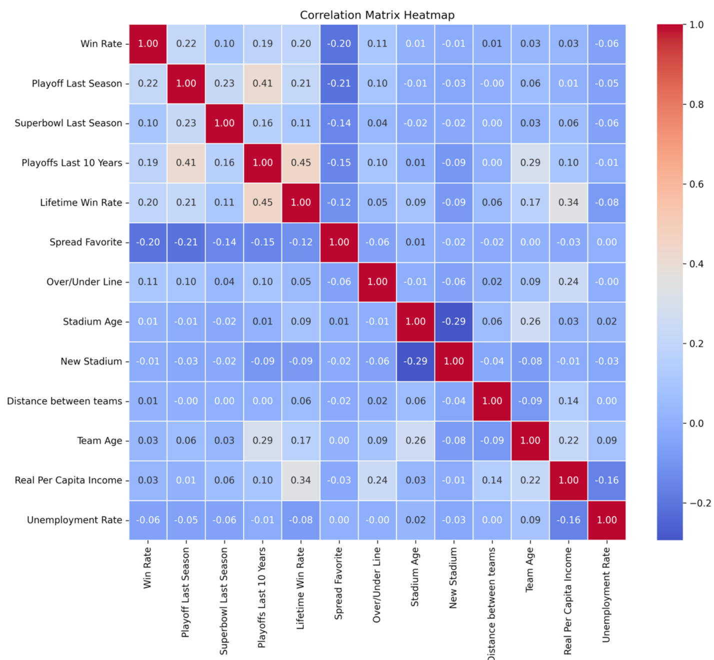

Figure 1 Correlation Matrix Heatmap of Variables

The correlation between New Stadium and Stadium Age is –0.29, indicating a mild inverse relationship, as expected. Overall, these results suggest that multicollinearity is not a significant concern in the empirical specification.

3. Empirical Results

Pooled OLS, fixed effects, and random effects models are initially employed to evaluate the model results, with each model offering distinct advantages. Pooled OLS provides a baseline estimation, aggregating data across entities and time without accounting for individual heterogeneity. Fixed effects models are used to control for time-invariant characteristics within entities, thus focusing on variations over time within the same entity. Random effects models, meanwhile, consider variation both within and across entities, assuming that the entity-specific effect is uncorrelated with the predictors. Model specification tests are subsequently conducted to ensure the appropriateness and robustness of these models in capturing the underlying dynamics[7].

3.1 Main Regression Results

Table 2 summarizes the regression estimates from the pooled OLS, fixed effects, and random effects models. Across all specifications, team performance variables consistently emerge as strong predictors of weekly stadium attendance. Current season winning percentage has a statistically significant and positive effect in all models, reinforcing the idea that fans respond dynamically to ongoing team success. Participation in the previous season's playoffs also boosts attendance, suggesting that recent relevance sustains fan engagement. Interestingly, winning the Super Bowl in the previous season exhibits a negative coefficient, which may reflect a psychological saturation effect, where heightened expectations dampen post-championship turnout. Long-term indicators such as lifetime win percentage remain significant across all models, implying a baseline fan loyalty driven by historical reputation. The medium-term measure, playoff appearances in the last ten years, is only significant in the fixed and OLS models, indicating that its influence may be absorbed by unobserved team-level traits in the random effects specification.

Turning to match-related factors, the effect of spread follows an inverted U-shape: extreme mismatches or guaranteed wins deter fan interest, while more balanced expectations (closer spreads) draw larger crowds. Similarly, higher over/under line values—a proxy for expected excitement and scoring—positively affect attendance. Among stadium characteristics, new stadiums significantly increase attendance, supporting the well-documented "honeymoon effect." Meanwhile, older stadiums slightly reduce turnout, possibly due to declining amenities. Geographic and economic variables also perform as expected. Attendance declines with greater distance between teams, while higher per capita income is associated with increased attendance, reflecting stronger discretionary spending power. Intriguingly, higher unemployment rates are positively correlated with attendance—suggesting that in some cases, sporting events may serve as a form of escapism during economic downturns.

Table 2. Impact of Various Factors Across Different Econometric Models

	Pooled OLS	**Fixed effect model**	**Random effect model**
Team Winning Percentage	4968.48***	4829.5***	3630.7***
Previous Season Playoff	2024.25***	1941.4***	1946.8***
Previous Season Super Bowl Winner	-2497.73***	-2033.9***	-2209.3***
Playoff Appearances (10 Years)	235.94***	238.28***	-27.66
Lifetime Winning Percentage	11630***	14170***	43930***
Spread	-8.98*	-9.0666*	-28.297***
Over/Under Line	171.84***	153.62***	334.82***
Stadium Age	-93.09***	-102.67***	-69.455***
New Stadium	1336.62***	1069.8**	2138.2***
Distance (km)	-0.43***	-16.762***	0.2225
Team Age	-96.82***	-47.961**	44.349***
Real Per Capita Income (USD)	131.32***	114.85***	104.59***
Unemployment Rate (%)	247.78***	198.69***	355.18***
Weekly dummies	Yes	Yes	Yes
Home team dummies	Yes	Yes	Yes
Road team dummies	Yes	Yes	Yes

Note: The significance of coefficients is denoted by asterisks, with "***" indicating $p < 0.01$, "**" indicating $p < 0.05$, and "*" indicating $p < 0.1$.

3.2 Model Selection Diagnostics

Table 3 presents the results of the Hausman and Breusch–Pagan tests, conducted to guide model specification. The Hausman test strongly favors the Fixed Effects model ($\chi^2 = 1150.31$, $p < 0.001$), indicating that unobserved team-level characteristics are correlated with the explanatory variables. This supports the use of Fixed Effects in subsequent analysis to control for time-invariant, team-specific factors.

Table 3. Specification tests: Fixed effects, random effects, and ordinary least squares

Test	Statistic	P-value
Hausman: FE versus RE	1150.31	8.30 e-237
Breusch–Pagan: RE versus OLS	1234.10	1.77 e-191

The Breusch–Pagan test ($\chi^2 = 1234.10$, $p < 0.001$) also rejects the pooled OLS in favor of Random Effects, suggesting that variance across teams is non-negligible. However, given the Hausman result, Fixed Effects are ultimately preferred for estimating the impact of predictors on attendance while minimizing omitted variable bias.

3.3 Temporal Dynamics of Attendance Responses

Table 4 explores how the effects of team performance on attendance vary across different phases of the season: early, middle, late, and playoff games. Notably, team winning percentage has a statistically significant impact in all periods but displays a dynamic pattern. In the early season, its effect is negative (β = –5983.70), suggesting that early wins alone may not attract larger crowds—possibly due to low confidence or uncertainty about team prospects. As the season progresses, the coefficient becomes positive and grows stronger, peaking during the playoffs (β = 4764.94), reflecting increased responsiveness as the stakes rise.

Table 4. Regression of NFL Attendance by Season Phases and Playoff Impact

	Early season	Middle season	Late season	Playoff
Team Winning Percentage	8332.6***	4363.7***	3715.3***	4764.9***
Previous Season Playoff	1741.1***	1811.5***	2017.7***	2070.8***
Previous Season Super Bowl Winner	-2276.2***	-1679.2**	-2267.5***	-1971.4***
Playoff Appearances (10 Years)	210.68***	215.43***	301.75***	256.85***
Lifetime Winning Percentage	11470***	14490***	13770***	13710***
Spread	-9.58*	-8.87	-9.41*	-9.14*
Over/Under Line	145.88***	151.69***	147.51***	154.2***
Stadium Age	-103.46***	-102.9***	-103.38***	-101.93***
New Stadium	994.30**	1067.2**	988.46**	1063**
Distance (km)	-16.88**	-16.99**	-16.531**	-16.79**
Team Age	-45.74*	-47.36*	-45.93*	-42.61*
Real Per Capita Income (USD)	115.38***	115.07***	115.14***	112.95***
Unemployment Rate (%)	200.71***	198.00***	197.69***	193.89***
Team winning percentage: period dummy	-5983.70***	1837.00*	7075.4***	2157.9
Last season playoff: period dummy	408.66	372.53	-406.22	-3421.3***
Last season super bowl winner: period dummy	461.57	-1163.30	743.72	-534.01
Playoffs in the last 10 years: period dummy	123.54	78.34	-163.67	-294.68
Life win percentage: period dummy	1667.20	-1854.90	-5008.5*	8586.3

Note: The statistical significance of coefficients is indicated by asterisks: "*** denotes $p < 0.01$, **denotes $p < 0.05$, *denotes $p < 0.1$."* For the purposes of this analysis, the NFL regular season is divided into three phases based on the standard 17-week schedule: 'Early season' encompasses the first six weeks, 'Middle season' spans weeks 7 to 12, and 'Late season' includes all subsequent regular season games. The 'Playoff season' is defined to include the wildcard, divisional, and conference championship rounds; the Super Bowl is excluded as it takes place in neutral venues.

The interaction between previous season playoff participation and the playoff period shows a surprising negative effect (β = –3421.3), potentially indicating a playoff saturation effect. Fans may become less enthusiastic when the novelty of postseason participation fades or when expectations are not met with deep playoff runs. This aligns with prior findings[4] that repeated postseason exposure without meaningful success can depress fan turnout. Period-specific dummies for other performance indicators similarly reveal nuanced temporal patterns. The lifetime win percentage dummy is positive and significant during the early and playoff periods, suggesting that legacy status draws consistent support, particularly at the start and peak of the season.

These findings underscore the importance of temporal context in fan behavior analysis: while short-term success matters, its influence intensifies only when fans perceive real stakes. Strategic marketing and ticket pricing may benefit from aligning with these seasonal attendance dynamics.

4. Conclusion

Drawing on 28 seasons and over 7,000 games, this study provides robust evidence on the dynamic relationship between NFL team performance and stadium attendance. Using a suite of panel data models, we disentangle the influence of performance indicators across multiple temporal dimensions—short-, medium-, and long-term—while controlling for stadium, geographic, economic, and match-level variables.

The findings underscore that team winning percentage is the strongest predictor of attendance, though its influence evolves across the season: initially negligible or negative, then gradually intensifying toward the playoffs. In contrast, previous postseason success, including Super Bowl victories, does not boost—and may even slightly dampen—subsequent season turnout. This suggests a fan fatigue or expectation saturation effect, where repeated high-stakes appearances no longer generate incremental interest. Structural factors also matter. New stadiums, higher expected scoring, and geographic proximity all increase attendance, while rising unemployment, paradoxically, also leads to modest gains—perhaps pointing to the escapist role of sports entertainment during economic downturns.

While the fixed effects model best captures the underlying dynamics, the study's reliance on historical averages limits its ability to reflect real-time shocks such as mid-season coaching changes or player injuries. Future work should integrate live performance tracking and finer-grained geographic and demographic data to capture fan behavior more precisely.

These insights hold practical value for team executives and league organizers aiming to sustain attendance across fluctuating seasons. Marketing efforts should be tailored to reinforce early-season engagement and offset expectation fatigue in high-performing franchises. Dynamic ticket pricing, enhanced in-stadium experiences, and seasonally targeted promotions may prove especially effective during late-season games, where attendance is most sensitive to team momentum.

This study, while comprehensive, is not without its limitations. The reliance on historical data and fixed effect models, although effective for this analysis, may not capture all nuanced effects, particularly those influenced by sudden changes in team management or unexpected economic factors. Future research could benefit from incorporating real-time data tracking to evaluate the impact of in-season changes on attendance. Additionally, expanding the dataset to include more granular demographic and geographic variables might offer deeper insights into localized fan behaviors. For stakeholders, the findings underscore the importance of consistent team performance and the potential negative impacts of high expectations following excessively successful seasons. Stakeholders should consider strategies that enhance fan engagement throughout the season and address factors that could offset the negative effects of increased unemployment rates on attendance. This study also highlights the need for dynamic pricing strategies and enhanced game-day experiences to sustain and grow attendance figures, particularly in the latter stages of the season when fan expectations and interest may wane.

Author's Contributions

Yu Pang: Methodology, Original Draft, Data Curation, Investigation, Visualization, Validation.

Fengchen Wang: Conceptualization, Analysis, Review & Editing. All authors approved the final version of the manuscript.

Conflict of Interest

The authors have no relevant financial or non-financial interests to disclose.

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