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WNBA attendance and the Clark/Resse effect

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Abstract

A surge of interest in the Women's National Basketball Association (WNBA) during the 2024 season has prompted media debate about the origins of the increased attention. This study employs a least squares approach on panel data to evaluate potential influences on game attendance while controlling for mitigating factors. The goal is to determine whether recent attendance growth is organic and the result of long-term efforts by players and league management or due to external factors such as the introduction of a popular rookie class, particularly Caitlin Clark and Angel Reese. Empirical results indicate that the surge is the result of a combination of these factors, with each contributing positively to varying degrees.

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1. Introduction

The 2024 Women's National Basketball Association (WNBA) season is on a scheduled break to allow for both the All-Star Weekend and the Olympic Games. This extended hiatus provides an opportunity for league players to participate in the Olympics and represent their respective countries. The WNBA is leveraging this period to highlight its talent on a global stage and broaden the game's visibility.

An enormous surge of fan interest and game attendance has been evidenced during the 2024 WNBA season. Following the escalation of interest, sports media has increasingly dedicated time to highlighting the WNBA. Just prior to the 2024 WNBA All-Star game, sports media pontificated on the origins of this attendance and interest spike. Some argue the increase results from organic growth and represents the natural progression of years of effort to promote the league by players and league management. Others speculate the 2024 rookie player class is the source. The 2024 rookie class is filled with talented players, but Caitlin Clark and Angel Reese garner most of the media attention.

To help provide clarity to the numerous conjectures, game attendance data are assembled in a panel format to identify contributing factors influencing attendance growth. This study aims to provide empirical evidence to support or refute these claims, using game attendance as a measure of broader fan interest.

2. Literature Review

The concept of estimating factors on influence of game attendance has a significant body of prior research. Seminal work in this field is established by Demmert (1973), Noll (1974), and Horowitz (1978), and the link between attendance and team success is recognized. They propose that the significant driver of game attendance is a high winning percentage. On-field success generates increased fan interest and higher attendance. Whitney (1988) in work consistent with this research further finds that the potential for potential postseason play can increase attendance.

Some exceptions to the established link between team success and attendance have been noted in subsequent research. Davis (2008) notes a dynamic component and maintains that the link is fleeting and quickly dissipates with time. Zimmer (2014, 2018) notes that the link diminishes at the extremes. Teams with constant success have lower attendance due to fan fatigue, while teams with long histories of on-field futility enjoy loyal fans and strong attendance. Other research on game attendance focuses on characteristics of play. For example, higher rates of home runs and better pitching yields better attendance in baseball (Greenstein & Marcum, 1981; Marburger, 1997; Horowitz, 2007).

3. Methodology

WNBA individual game statistics (ESPN, 2024) are assembled in a panel dataset. The study examines full season data from 2018 through 2023, excluding the 2020 season as its was played in isolation at a neutral site with no fan attendance due to the Coronavirus pandemic. Data from the 2024 season are included up to the All-Star/Olympic break and represents approximately 50-60% of 2024 season games. The study includes regular season games while excluding both pre-season and post-season games. A list of teams is found on Table 1.

Table 1

Teams

Eastern Conference	Western Conference
Atlanta Dream	Dallas Wings
Chicago Sky	Los Vegas Aces
Connecticut Sun	Los Angeles Sparks
Indiana Fever	Minnesota Lynx
New York Liberty	Phoenix Mercury
Washington Mystics	Seattle Storm

WNBA data are collected for home games. The data include game attendance (Attend). Some attendance data are not available. This is particularly true for the 2021 season as teams re-started normal operations. A total of 1,188 observations are collected, of which 1,168 are complete.

Variables that may influence game attendance are also collected, including variables to assess media speculation. Seasonal binaries (S2018, S2019, S2021, S2022, S2023, S2024) are added to assess the yearly impact on game attendance. The variables are designated as affirmative (1) in their respective seasons. The variables should be help in assessing the potential of yearly organic attendance growth. Again, the 2020 season is excluded due to the pandemic and the 2024 season represents only a partial season.

A proxy is created to estimate the impact of individual players on game attendance. A composite binary variable is created for the team on which the athlete plays and the year in which the athlete played. The Clark Home Effect (CHE) is designated as affirmative (1) for Indiana Fever home games during the 2024 season. The Clark Away Effect (CAE) is designated as affirmative (1) for Indiana Fever away games during the 2024 season. The Reese Home Effect (RHE) is designated as affirmative (1) for Chicago Sky home games during the 2024 season. The Reese Away Effect (RAE) is designated as affirmative (1) for Chicago Sky away games during the 2024 season. These variables assess the game attendance impact of Clark and Reese assuming most of their respective team effects are due to these individual players.

Control variables are included to account for other game attendance influences. Binaries variables are included to represent the first (First) and last (Last) home game of each season as they might generate public excitement. The variables are designated as affirmative (1) for those games. It is possible that weekend and holiday games attract higher levels of attendance as people might have more free time to spend on leisure/entertainment activities. A weekend binary (Weke) variable is created and is designated as affirmative (1) if a game is played on Friday, Saturday or Sunday. A Holiday binary (Hol) is created and is designated as affirmative (1) if a game is played on a national holiday or the prior day. The applicable federal holidays include Memorial Day, Juneteenth (starting 2021), Independence Day, and Labor Day.

As noted in literature, fans often respond to team success. A better home team can attract more fans to attend games. The home team winning percentage (HTWP) represents the quality of play for a team for a particular season. Likewise, if a visiting team is playing well, fans may attend to see the away team. The away team winning percentage (ATWP) represents the quality of the visiting team.

Fans have many options for leisure/entertainment/sports that vie for this attention. These competing options vary during the year as many sports and interests are seasonal. To account for seasonal differences and the potential for variation in competition from other leagues and activities for fan interest, monthly binaries (May, Jun, Jul, Aug, Sep) are created. They are designated as affirmative (1) in the month in which a game is played.

Binaries are created to represent the home team for each game. Markets differ by population, demographics, and general team interest/loyalty. Each market is unique, and these binaries (AtlH, ChiH, ConH, IndH, NYH, WasH, DalH, LVH, LAH, MinH, PhoH, SeaH) control for the location specific differences in the home markets. They are designated as affirmative (1) for the home team.

Finally, binaries are created to represent the away team for each game. These binaries account for the potential of a team to consistently attract higher or lower attendance as the away team. It is possible a team maintains a fanbase that will travel or maintains a national presence that will draw fans in competing markets. The binaries (AtlA, ChiA, ConA, IndA, NYA, WasA, DalA, LVA, LAA, MinA, PhoA, SeaA) control for a team's ability to increase or decrease attendance in other markets. They are designated as affirmative (1) for the away team.

Summary statistics for all variables are provided on Table 2.

Table 2

Summary Statistics

	Dependent Variable	Notation	Obs.	Mean	Std. Dev.	Min.	Max.
1	Game Attendance	Attend	1,168	6,287.4	3,507.1	301	20,366
	Independent Variables	Notation	Obs.	Mean	Std. Dev.	Min.	Max.
1	Season 2018	S2018	1,188	0.171	0.377	0	1
2	Season 2019	S2019	1,188	0.172	0.377	0	1
3	Season 2021	S2021	1,188	0.148	0.355	0	1
4	Season 2022	S2022	1,188	0.182	0.386	0	1
5	Season 2023	S2023	1,188	0.202	0.402	0	1
6	Season 2024	S2024	1,188	0.125	0.331	0	1
7	Clark Home Effect	CHE	1,188	0.009	0.096	0	1
8	Clark Away Effect	CAE	1,188	0.013	0.112	0	1
9	Reese Home Effect	RHE	1,188	0.011	0.104	0	1
10	Reese Away Effect	RAE	1,188	0.003	0.100	0	1
Control Variables							
11	First Home Game	First	1,188	0.598	0.237	0	1
12	Last Home Game	Last	1,188	0.060	0.237	0	1
13	Weekend	Weke	1,188	0.568	0.496	0	1
14	Holiday	Hol	1,188	0.568	0.496	0	1
15	Home Team Win %	HTWP	1,188	0.506	0.179	0	0.850
16	Away Team Win %	ATWP	1,188	0.497	0.181	0	0.850
17	May	May	1,188	0.160	0.367	0	1
18	June	Jun	1,188	0.319	0.466	0	1
19	July	Jul	1,188	0.246	0.431	0	1
20	August	Aug	1,188	0.210	0.408	0	1
21	September	Sep	1,188	0.063	0.243	0	1
22	Atlanta Home	AtlH	1,188	0.083	0.277	0	1
23	Chicago Home	ChiH	1,188	0.085	0.279	0	1
24	Connecticut Home	ConH	1,188	0.085	0.279	0	1
25	Indiana Home	IndH	1,188	0.070	0.255	0	1
26	New York Home	NYH	1,188	0.085	0.279	0	1
27	Washington Home	WasH	1,188	0.083	0.277	0	1
28	Dallas Home	DalH	1,188	0.083	0.277	0	1
29	Las Vegas Home	LVH	1,188	0.085	0.279	0	1
30	Los Angeles Home	LAH	1,188	0.084	0.278	0	1
31	Minnesota Home	MinH	1,188	0.086	0.280	0	1
32	Phoenix Home	PhoH	1,188	0.084	0.278	0	1
33	Seattle Home	SeaH	1,188	0.086	0.280	0	1
34	Atlanta Away	AtlA	1,184	0.084	0.278	0	1
35	Chicago Away	ChiA	1,184	0.084	0.278	0	1
36	Connecticut Away	ConA	1,184	0.080	0.272	0	1
37	Indiana Away	IndA	1,185	0.088	0.283	0	1
38	New York Away	NYA	1,184	0.084	0.277	0	1
39	Washington Away	WasA	1,188	0.084	0.278	0	1
40	Dallas Away	DalA	1,184	0.085	0.279	0	1
41	Las Vegas Away	LVA	1,184	0.082	0.274	0	1
42	Los Angeles Away	LAA	1,184	0.084	0.277	0	1
43	Minnesota Away	MinA	1,183	0.083	0.276	0	1
44	Phoenix Away	PhoA	1,185	0.083	0.276	0	1
45	Seattle Away	SeaA	1,186	0.082	0.274	0	1

Equation 1 represents the ordinary least squares model. The dependent variable is game attendance (*Attend*). Independent variables include seasonal binary variables (*S2018, S2019, S2021, S2022, S2023, S2024*), Clark home and away effect binary variables (*CHE, CAE*), Reese home and away effect binary variables (*RHE, RAE*), and control variables including first and last home game binary variables (*First, Last*), weekend and holiday game binary variables (*Weke, Hol*), winning percentages of home team (*HTWP*) and away team (*ATWP*), monthly binary variables (*May, Jun, Jul, Aug, Sep*), home team binary variables (*AltH, ChiH, ConH, IndH, NYH, WasH, DalH, LVH, LAH, MinH, PhoH, SeaH*) and away team binary variables (*AltA, ChiA, ConA, IndA, NYA, WasA, DalA, LVA, LAA, MinA, PhoA, SeaA*)

$$\begin{aligned}
Attend_{s,t,g} = {} & \beta_0 + \beta_1(S2018_s) + \beta_2(S2019_s) + \beta_3(S2021_s) + \beta_4(S2022_s) + \beta_5(S2023_s) \\
& + \beta_6(S2024_s) + \beta_7(CHE_{s,t}) + \beta_8(CAE_{s,t,g}) + \beta_9(RHE_{s,t,g}) + \beta_{10}(RAE_{s,t,g}) \\
& + \beta_{11}(First_{s,t,g}) + \beta_{12}(Last_{s,t,g}) + \beta_{13}(Weke_{s,t,g}) + \beta_{14}(Hol_{s,t,g}) \\
& + \beta_{15}(HTWP_{s,t,g}) + \beta_{16}(ATWP_{s,t,g}) + \beta_{17}(May_{s,t,g}) + \beta_{18}(Jun_{s,t,g}) \\
& + \beta_{19}(Jul_{s,t,g}) + \beta_{20}(Aug_{s,t,g}) + \beta_{21}(Sep_{s,t,g}) + \beta_{22}(AtlH_{s,t,g}) \\
& + \beta_{23}(ChiH_{s,t,g}) + \beta_{24}(ConH_{s,t,g}) + \beta_{25}(IndH_{s,t,g}) + \beta_{26}(NYH_{s,t,g}) \\
& + \beta_{27}(WasH_{s,t,g}) + \beta_{28}(DalH_{s,t,g}) + \beta_{29}(LVH_{s,t,g}) + \beta_{30}(LAH_{s,t,g}) \\
& + \beta_{31}(MinH_{s,t,g}) + \beta_{32}(PhoH_{s,t,g}) + \beta_{33}(SeaH_{s,t,g}) + \beta_{34}(AtlA_{s,t,g}) \\
& + \beta_{35}(ChiA_{s,t,g}) + \beta_{36}(ConA_{s,t,g}) + \beta_{37}(IndA_{s,t,g}) + \beta_{38}(NYA_{s,t,g}) \\
& + \beta_{39}(WasA_{s,t,g}) + \beta_{40}(DalA_{s,t,g}) + \beta_{41}(LVA_{s,t,g}) + \beta_{42}(LAA_{s,t,g}) \\
& + \beta_{43}(MinA_{s,t,g}) + \beta_{44}(PhoA_{s,t,g}) + \beta_{45}(SeaA_{s,t,g}) + \epsilon
\end{aligned} \tag{1}$$

$$where\ s = season, t = team, g = game$$

The model contains many explanatory variables giving rise to the potential for multicollinearity and overfitting which may affect the interpretability of individual coefficients. Variance inflation factor (VIF) is included to assess the potential of multicollinearity to influence the results.

4. Results

Model results are provided on Table 3. Some variables are omitted for collinearity. Levels of statistical significance are 1% and 5%. The dependent variable is game attendance (Attend) and independent variables are assessed for influence. The overall model is highly significant (F=55.47, $p < 0.0001$). The diagnostic tests (VIF values) indicate the potential for multicollinearity issues are low/modest.

Table 3

Least Squares Model

			Coef.	S.E.	VIF
Dependent Variable and Notation					
	Game Attendance	Game			
Independent Variables and Notation					
1	Season 2018	S2018		omitted	
2	Season 2019	S2019	-340.7	209.1	1.7
3	Season 2021	S2021	-4,217.3 **	224.8	1.7
4	Season 2022	S2022	-962.3 **	205.1	1.7
5	Season 2023	S2023	-218.4	199.9	1.8
6	Season 2024	S2024	1,448.4 **	258.8	2.1
7	Clark Home Effect	CHE	9,994.1 **	706.2	1.3
8	Clark Away Effect	CAE	7,007.2 **	618.8	1.3
9	Reese Home Effect	RHE	265.1	650.7	1.3
10	Reese Away Effect	RAE	1,853.9 **	673.1	1.3
Control Vaiables					
11	First Home Game	First	1,150.4 **	313.4	1.5
12	Last Home Game	Last	1,278.4 **	299.6	1.3
13	Weekend	Weke	341.2 **	126.5	1.1
14	Holiday	Hol	-188.3	282.0	1.1
15	Home Team Win %	HTWP	4,088.6 **	429.1	1.6
16	Away Team Win %	ATWP	1,133.2 **	423.9	1.6
17	May	May	-522.5 *	220.0	1.8
18	June	Jun		omitted	
19	July	Jul	869.3 **	163.5	1.4
20	August	Aug	738.4 **	177.8	1.5
21	September	Sep	671.2 *	310.2	1.6
22	Atlanta Home	AtlH	-1,342.6 **	329.6	2.3
23	Chicago Home	ChiH	1,503.9 **	353.2	2.6
24	Connecticut Home	ConH	39.7	374.1	3.0
25	Indiana Home	IndH		omitted	
26	New York Home	NYH	194.5	337.1	2.5
27	Washington Home	WasH	-661.2	345.1	2.5
28	Dallas Home	DalH	-591.1	331.9	2.3
29	Las Vegas Home	LVH	732.2 *	372.8	2.8
30	Los Angeles Home	LAH	2,746.7 **	333.9	2.4
31	Minnesota Home	MinH	2,406.7 **	343.0	2.6
32	Phoenix Home	PhoH	4,060.9 **	334.1	2.4
33	Seattle Home	SeaH	2,703.3 **	348.2	2.7
34	Atlanta Away	AtlA	18.8	302.6	2.0
35	Chicago Away	ChiA	-184.9	307.6	2.0
36	Connecticut Away	ConA	-470.4	308.5	2.0
37	Indiana Away	IndA	106.3	330.4	2.4
38	New York Away	NYA	82.5	299.7	1.9
39	Washington Away	WasA	-188.8	297.8	1.9
40	Dallas Away	DalA	-273.8	303.1	1.9
41	Las Vegas Away	LVA	262.6	306.8	1.9
42	Los Angeles Away	LAA	373.8	301.0	1.9
43	Minnesota Away	MinA		omitted	
44	Phoenix Away	PhoA	393.6	300.7	1.9
45	Seattle Away	SeaA	224.5	301.1	1.9
	constant			2452.7	

F (41 , 1121) = 55.47

Prob > F 0.0000

Observations 1,163

*Statistical Significance: * 5%, ** 1%*

The yearly binary variables are significant in 2021, 2022 and 2024. The Coronavirus pandemic has a profoundly negative and long-lasting influence on league attendance. The 2020 season was played in isolation without fans. Fans are shown to be reluctant to return afterward. The coefficients on the 2021 and 2022 binary variables (*S2021, S2022*) are negative and statistically highly significant. The change in attendance due to the yearly impact of the pandemic is a reduction of per game attendance by approximately 4,217 fans. The devastating influence improves slightly for the 2022 season, but the yearly impact on attendance is still negative and reduces per game attendance by approximately 962 fans. The league recovers by the 2023 season as the coefficient of the yearly binary variable is statistically insignificant.

The coefficient of the yearly 2024 binary variable (*S2024*) is statistically highly significant and positive. The yearly positive influence on per game attendance during the 2024 season is approximately 1,448 fans. This is evidence of organic attendance growth. When controlling for all other variables, league per game attendance grew. After taking several seasons to recover from the pandemic and lure fans back the WNBA, 2024 provides empirical evidence for the beneficial contribution of efforts to promote the league. The yearly effects on game attendance are provided on Table 4.

Table 4

Yearly Attendance Benefit

WNBA Season	Per Game Effect
2018	
2019	
2021	-4,217.7
2022	-962.3
2023	
2024	1,448.4

statistically significant results

The coefficients of both the Clark home effect (*CHE*) and away effect (*CAE*) are statistically highly significant and positive for the first portion of the 2024 season. For home games, Clark increases per game attendance by approximately 9,944 fans. For away games, Clark increases per game attendance by approximately 7,007 fans in the visiting markets. The results provide empirical evidence of the strength of the Clark effect. Many Indiana Fever games (particularly home games) are sold out in 2024. Stadium capacity thus creates an upper bound on this variable. The Clark effect might be larger but is being limited by the capacity of stadiums to accommodate more fans.

The coefficient of the Reese home effect (*RHE*) is not statistically significant, but the coefficient of the away effect (*RAE*) is highly significant and positive for the first portion of the 2024 season. For away games, Reese increases per game attendance by approximately 1,854 fans in the visiting markets. The results provide empirical evidence of the Reese effect. It is surprising to find that the Reese effect is greater in visiting markets, suggesting her appeal is greater nationally than locally.

Control variables are added to account for other potential influences on game attendance. The coefficients of the first (*First*) and last (*Last*) home games each season are both statistically highly significant and positive. Excitement for the first home game of the season generates an increase in game attendance of approximately 1,150 fans. The final home game of the season generates an increase in game attendance of approximately 1,278 fans.

Consistent with prior research, WNBA fans are generally attracted to winning teams. The coefficients of both the home team winning percentage (*HTWP*) and the away team winning percentage (*ATWP*) are statistically highly significant and positive. Game attendance increases if the home team is having a successful season. Winning generates excitement in the home market. Additionally, if the visiting (away) team is good, more people will attend games to view quality opponents.

The coefficients of the monthly binaries (*May, Jul, Aug, Sep*) are statistically significant. The month of May negatively impacts game attendance. The months of July, August and September positively influence game attendance. The relative impact of each month on game attendance is provided on Table 5.

Table 5

Monthly Attendance Benefit

Team	Benefit
May	-522.5
June	
July	869.3
August	738.4
September	671.2

statistically significant results

The coefficients of the home game binary variables are statistically significant and positive for 6 teams and negative for 1 team. In 6 markets, the metro size, demographics, regional income levels, community support, brand loyalty or other factors provide a team with a better game attendance. The teams in 5 markets have no statistical significance and do not get the benefit of increased attendance. One market has a negative effect which suppresses game attendance. The relative impact of each market on game attendance is provided on Table 6.

Table 6

Home Team Attendance Benefit

Team	Benefit
Phoenix	4,060.9
Los Angeles	2,746.7
Seattle	2,703.3
Minnesota	2,406.7
Chicago	1,503.9
Las Vegas	732.2
Connecticut	
Dallas	
Indiana	
New York	
Washington	
Atlanta	-1,342.6

statistically significant results
listed in oder of benefit

Phoenix enjoys the strongest favorable attendance bias even though it is not the largest or most affluent market. Points of concern include Atlanta, which has a negative attendance bias suppressing attendance and suggesting more efforts required to engage the local market. Also interesting are the statistically insignificant markets. In particular, New York represents the largest metro in the league with high affluence, yet the team is unable to convert this massive advantage into a favorable attendance bias. None of the away team coefficients are statistically significant. No team is able generate consistently higher or lower attendance rates when traveling as the away team.

The results on the team binaries (both home and away) are an interesting as they do not appear to correlate with the population size of the team's surrounding metro area. It might be expected that teams near population centers would enjoy larger attendance, but the results suggest less of an impact. While the VIF numbers for these variables are slightly elevated, it is unlikely that multicollinearity is the source of this finding. Future research is needed as this finding seems contrary to expectations and prior research.

5. Discussion

It is perhaps overly simplistic to assume the recent surge in WNBA game attendance and overall league interest could be distilled down into a single source. The results empirically show that attendance growth is the result of several factors contributing at various levels to produce a positive outcome.

The pandemic was an especially troubling time for the WNBA. It took several years and significant promotional efforts to recover. Thankfully, the 2024 WNBA season is witnessing a surge of fan interest and game attendance.

The results indicate the yearly organic growth on per game attendance is approximately 1,448 after accounting for other factors. This represents healthy growth resulting from the promotional activities of league management and player activities over multiple seasons.

At the same time, the Clark/Reese effect is also very real. Clark is shown to be the dominant driver of increased attendance within the WNBA and contributes an increase of approximately 9,994 fans to home games and 7,007 fans to away games. Reese contributes approximately 1,854 fans to away games. These increases are substantial and clearly indicate the positive contribution of these players.

The results provide empirical evidence that growth in WNBA game attendance comes from multiple sources. While Clark is the largest contributor, growth is simultaneously the result of organic growth and the Reese effect. Not only are they all beneficial influences, but it is very likely that these factors produce positive results in a symbiotic and co-dependent manner. With increased time, data and more complex methodology, the interdependent relationship between these factors might be more thoroughly explored in future research.

The larger task for WNBA management is to capitalize on the surge. The waves of increased game attendance resulting from the Clark/Resse effect at particular games implies fans that are loyal to these players, but not necessarily of the WNBA. The goal is to use the opportunity to illustrate the quality of league play and make them simultaneously fans of both the players and the WNBA. The National Basketball Association (NBA) has a long history of successfully marketing numerous athletes that have entered the league and captured public attention. The NBA effectively converted interest in the individual players into fans of the overall league. The WNBA needs to do the same and ensure that the rising tide lifts all boats.

The focus of this study is game attendance. It is acknowledged that WNBA management must take a boarder view and consider all revenue opportunities and constraints when making decisions. To maximize overall revenue, attendance is balanced with broadcasting and merchandising. It is possible that what provides the highest game attendance might not coincide with what is best for broadcasting or merchandising efforts. League management must balance all considerations when making decisions.

Finally, future research can investigate the full degree of the Clark effect as attendance data is limited by stadium capacity. It is likely that the effect has a larger magnitude and is better appreciated and understood when studied using broadcasting data. Viewship data is unlikely to suffer the same upper bound limitation of attendance, allowing the effect to be more fully exhibited and measured to better understand it's potential scope.

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