Mid-Season Interruption: Did the FIFA Women’s World Cup and the ESPN broadcasting agreement effect NWSL attendance?

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After the disbandment of the Women’s Professional Soccer (WPS) in 2012, the National Women’s Soccer League was created in that same year with much optimism. Although the NWSL has had many successes over the years compared to other professional women’s soccer leagues, the NWSL has had a lot of difficulty with broadcasting agreements and maintaining attention from fans. This essay seeks to analyze the effect broadcasting agreements and the FIFA WWC had on NWSL attendance. I find that there are statistically significant changes in attendance from the events of the FIFA’s Women’s World Cup and the broadcasting agreement between the NWSL and ESPN in the year 2019.
1. *Introduction*

At just seven years old, the National Women’s Soccer League (NWSL) is the longest running professional women’s soccer league in the world. As a third try from the United States Soccer Federation for a successful women’s soccer league, the NWSL is comprised of nine Division-1 teams with players from all around the globe (Rollins, 2017). The NWSL was the first American women’s soccer league to survive past the fourth season (Rollins, 2017). Yet compared to men’s leagues the NWSL is still in its infancy. Despite its early stages, the league has sustained a steady attendance rate each season, but it’s not growing fast enough to stay profitable. The NWSL has had to drop multiple teams to continue to make the league cost effective. Growing a league means that it needs to increase the fanbase, sponsors, and broadcasting agreements. Unlike the professional men’s US league, known as Major League Soccer (MLS), who has multiple broadcasting agreements all over the world. The NWSL has had seasons without even one broadcasting agreement. In the MLS 2019 season they averaged 21,310 for their attendance, almost tripling the NWSL attendance at just 7,337. With the age of the MLS more than three times that of the NWSL, it makes sense that the MLS would have a larger fan base, more reputable sponsors, bigger venues, and more teams. Although the men’s soccer has been prevalent for so long, the women’s side of the sport is starting to take some of the spotlight. The US Womens National Team (USWNT) has a long history of breaking records for the US Soccer Federation and breaking barriers for women. The final between the US and Japan holds the record for the most watched soccer game men’s or women’s in US history during the 2015 Women's World Cup. The game averaged 23 million viewers beating the NBA and Stanley Cup finals ratings (Chappell, 2015) (Hinog, 2015). Also, during the 2019 FIFA Women's World Cup, the USWNT home jersey was a record-breaking seller on Nike’s official retail site (Sports News,
With the added attention on women’s soccer at the national level there is some reason to believe their popularity from major tournaments could follow them back to the NWSL, where the entire USWNT plays and several other world class players like Sam Kerr, Marta, Rachel Daly, Rachel Corsie, Christine Sinclair, etc. There is no shortage of talented players in NWSL, but there are shortcomings with the leagues ability to present their games to fans. Broadcasting has become a major influence in making a league popular. The NWSL has had to be adaptive and strategic when finding companies to broadcast their sport. For the first three years of the NWSL life they could only manage to sign one-year contracts with less than half of their games actually broadcasted from major networks like ESPN and Fox Sports. For those years the NWSL mostly relied on streaming their own games through their YouTube channel and the NWSL website. In 2017 a three-year agreement was signed with A&E Networks to broadcast 25 matches through A&E’s Lifetime Network and another agreement with GO90 for the rest of the matches (Anderson, 2017) (Das, 2017). The Lifetime network hadn’t broadcasted sports since the early 2000’s for the WNBA. Despite the fact the networks weren’t known for sports entertainment, it was the NWSL’s first time they had a game broadcasted every week from a major network. Although the three-year contract may have felt like a big break for the league, they got a lot of backlash from the fans and players. The NWSL suffered a great deal of fan anger with games featured on GO90 being riddled with technical difficulties (Bush, 2017) (Rollins, 2017). Not only did the league have problems with fans about broadcasting quality, they also faced resistance from players for their safety. After Rachel Daly, a Houston Dash Forward, collapsed during a Game of the Week scheduled during the hottest time of the day (Burke, 2017), The leagues players pushed for safer game times. Not long after, broadcasted games were adjusted for longer durations to allow for hydration breaks, games not scheduled for
broadcasting were set for safer times to play, and additional procedures were incorporated to ensure player safety and match scheduling. In the league’s 2018 season GO90 announced they would cease broadcasting for the NWSL (Goldberg, 2018). On February 20th, 2019 the NWSL announced that A&E were pulling out of their three-year broadcasting agreement (Kassouf, 2019). In the beginning of the 2019 season the NWSL league didn’t have a national TV deal. With the uncertainty of a deal for the season the Chicago Red Stars, a NWSL team, made their own TV deal with Chicago NBC in July of 2019. During the same month, the NWSL and ESPN announced a broadcasting agreement with a 14-game package for the rest of the season. An agreement with a longstanding and distinguished broadcaster had fans pleased that the league finally made a quality streaming deal, although it was just for half a season. Not long after the short-term agreement was signed the NWSL announced a multimedia agreement for exclusive worldwide rights with ESPN for regular season games (Levine, 2019). The latest ESPN agreements could provide a way for the league to grow faster and establish a more reliable name for the NWSL.

a. Literature Review

According to economic principles one of the determinants of demand are substitutes and compliments. An essay done by Stephen Allan running multiple regressions found that a game that included a live streaming had a lower attendance than games that did not offer live streaming (Allan, 2004). The data used in the model was taken from premier league seasons. The model found the live stream variable to be a substitute with attending a football match. Although the demand principle stands true in this paper, the NWSL has not been around as long as many of the men’s leagues. I want to determine if a quality broadcasting agreement with the NWSL could prove a compliment to the league. The league is very young, and they have such a small fan base
that I would expect a reliable TV broadcasting agreement to increase their fan base and attendance. I could also see as the league grows and becomes less focused on creating a fan base and more on creating more profits, streaming and attendance could become more like substitutes. Grant Allan and Graeme Roy examined the Scottish Premier to see if TV broadcastings affected on attendance. They expressed that broadcasting has not been found to prove an economic reward or failure with teams in the long run. They also explained that broadcasting could prove less important to major leagues and more important to smaller leagues (Allan and Roy, 2008). This paper was vital in following their procedures due to both the Scottish and NWSL league being small leagues and finding broadcasting agreement very hard to acquire. The authors were lucky in gaining access to a dataset with large sets of information from the Scottish Premier League. The NWSL data were less abundant. They found that live television broadcasting was less of an influence on attendance than they previously anticipated (Allan and Roy, 2008). Although the leagues proved to be small in comparison to other leagues, much of the factors they chose to determine attendance were not factors that the NWSL has information on or is old enough to have yet. More examinations on women’s sports could provide more input as to what factors affect attendance than even small men’s leagues.

The majority of studies have been on men’s sports, explains Shackelford and Greenwell in their essay specialized for women’s sports and what factors affect attendance (Shackelford and Greenwell 2005). Although the essay used factors more targeted to college sports such as student enrollment, city population, competition level of other universities, and the teams winning percentage from previous season, concepts from their variables can be used to create ties with professional leagues. Data collected from Shackelford and Greenwell’s essay, were from multiple women’s sports from the Division I schools. Many of the factors the essay uses are not
readily available for the professional sports not supported by Title IX. Given that some of the NWSL teams don’t have a set home venue, it made it difficult to estimate the amount of the population the NWSL teams should incorporate. Competition level is another great variable many professional leagues can use to help explain attendance between rivalries. Because it is small, there are too few rivalries in the league to be included in models to prove efficient with understanding variation in attendance. Without a Title IX for professional leagues many of the measurable variables used in the college sports papers do not reflect women’s sports. This essay will find other variables that can be used to explain variations in the regular season attendance in a women’s professional league with less resources and stats than men’s leagues.

Much of the literature on sports is focused on men’s leagues. Very few articles are focused solely on women’s leagues, especially with the effects on attendance. There aren’t any studies on the NWSL, in part because they have only been around for seven years and they are a women’s league. This article looks to break the habit of focusing on data rich men’s sports and rather, focus on a record-breaking women’s league concentrated on keeping women’s sports relevant.

2. Data

I retrieved data from a public data website FBref. FBref is an organization of multiple sites that provide statistics and resources to anyone that wants information about a variety of sports. Data from the NWSL regular seasons were collected and used to analyze and interpret the models explained in later sections of the essay. Post season data were kept out to retain common fan attendance over the electrified fan behavior and attendance for semi-finals and championships matches. Data were condensed to six variables: day of the week the game was played, date, home team, away team, venue, and attendance. 2018 and 2019 season data will be the only data used in the model section, due to the fact that 2018 was the most consistent year for
broadcasting. This allows for the most accurate comparison in the models. Attendance wasn’t recorded for the years 2014 and 2015. Because the entire population data for the two years were missing, and they didn’t influence the model section they were dropped from the summary stats in the paper.

\[ a. \] Variables

The “week_day” variable was kept for a better understanding of the variation when games were played and to see if certain days had an effect on attendance. Weekends were expected to have a larger effect on attendance than games in the middle of the week. From Table 2 over 80% of the 2018 and 2019 season games were played during the weekend (consisting of Friday, Saturday, and Sunday). (I included Friday as part of the weekend because games on a Friday will typically be the start of the fan’s weekend, rather than before a fan finishes their workweek.) The rest of the games are played during the week with almost 90% of games during the week being played on a Wednesday.
Dates were kept in the data set for the model section. The date information was crucial in determining if the events from the FIFA Women’s World Cup and ESPN’s broadcasting agreement affected the attendance of the 2019 season. There are two games recorded without any attendance data from 2013 and 2016, but there is no need to estimate if the missing data created a bias in the model because the model only used the 2018 and 2019 regular season data.

The home and away team variables were used to determine if certain teams bring in more fans than others. The home and away team information allowed for holding the team name constant in the model. Although rank would have been a valuable variable to have for the model section to also keep as a constant term to eliminate attendance bias, home and away data will suffice. The ranking of the teams in the 2018 and 2019 season were fairly similar. The top four teams are all

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the same in both seasons just in a different order. Similarly, the fifth through last placed teams are all the same, but in different orders in both NWSL seasons.

Venues are kept in the dataset because each of them has a specific capacity. Each venue is matched with the stadium’s capacity. I found the stadiums capacity for each team from wikipedia.org. Because some of the NWSL teams don’t have an official long-term stadium, they change venues during the season often. This is why there is not a dataset with listed capacities on NWSL venues. For this reason, merge was not an option with venue capacities. Instead individual inputs were required for each venue’s capacity. After creating a capacity variable for each stadium, I determined how close a team was to reaching their stadium’s capacity and fix this variable for comparisons. This information could provide crucial for policy decision from the NWSL teams in determining if an expansion to their current stadium or of a new stadium would fit demand. Another reason for the capacity variables is for a fixed effect on capacity when comparing team’s attendance. Take for example the Portland Thorns and North Carolina Courage. Although these teams are very similar with star players and rankings, they are different in venue capacities. The Portland Thorns have a large capacity venue and the North Carolina Courage have a medium capacity venue. With holding venue capacity constant, I was able to compare the teams and their attendance. An estimate can now be made with the North Carolina Courage to see if they would have a more similar attendance to the Portland Thorns if venue capacity was fixed. As shown in the graph below there is a definite difference in attendance between the two teams, but instead of assuming that one team just has a better fanbase, ranking, marketing, etc. the effect of venue capacity can now be a factor.
The variables small, medium, and large were created from venue capacities, where small stadiums had a maximum capacity less than 10,000, medium capacity was between 10,000 and 22,000, and greater was anything larger than 22,000.

Since the attendance variables were one of the most important parts of these data, I used them in all of my models. A complete population for attendance data is used for the 2018 and 2019 regular seasons, this ensures no sample bias. To understand the effects on attendance better, I made the attendance a natural log to account for percent changes and not unit/person changes in the variable for the models.

A broader examination of the summary stats of the NWSL’s attendance from the past seven years is given in Table 3. The attendance averages appear to be predominantly increasing each year. This could be further evidence that the league is in fact growing each year. Along with the means, the standard deviations from Table 3 indicates that the variation in attendance is also increasing. This indicates that although the overall population attendance is increasing there could be teams still that are having a difficult time increasing their attendance each season.
Table 3

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<td>5082.92</td>
<td>6023.72</td>
<td>7385.70</td>
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The graph below is another examination to the NWSL attendance over its lifespan. The graph shows each year’s average attendance and includes a trend line to illustrate the overall trend the league has had with their attendance growth.

When looking below at the individual season attendances for the years 2018 and 2019 it’s easy to spot an increasing steep trendline in the 2019 graph. Just comparing the two season’s slope could help illustrate why there is a consideration if the FIFA Women’s World Cup and an ESPN broadcasting agreement had an effect on the steeper sloped attendance on the 2019 season.
3. Model

Before the models were created to see if events through the 2019 season affected attendance, I checked the four assumptions of multivariable econometrics to be sure the models would be accurate and hold reliable information.

1. **Linear in parameters**

   As will be shown in this section, the variables will not all be linear due to the requirement of a difference in difference model to estimate event effects. The parameters in every model used below are linear, allowing me to solve a system if linear equations.

2. **Random sampling**

   Because I have the entirety of the 2018 and 2019 regular season data, there is no reason to assume a sample bias on the population.

3. **No multicollinearity**

   Each model being used has some of the independent variables to explain attendance with some inter-associations from the left side of the model. The variables responsible for the multicollinearity are venue capacity and home teams. With only three out of the nine NWSL
teams that use more than one venue throughout the seasons there are bound to be correlations between the variables.

If I were to leave out the home variable from the models lots of the variation in NWSL’s attendance would not be explained. When adding the home variable to the first model below, there is a 60% jump in the variation explained by home team.

With the addition of the home variable bringing a large increase in the variation of attendance explained, the standard errors for the capacities grow larger as well, especially the large capacity variable. This rise in the standard errors is caused by the fact that most of the teams that use the large capacity venues don’t change venues throughout the season, leaving a major portion of home team and venue capacity with collinearity.

Although this spike in standard errors for capacity and home team is a problem, the real question in the paper is to see if events through the 2019 season affected attendance. To solve this with the smallest standard errors and largest variation of attendance explained the variable for home will stay in the model. Later in this section I will show the difference in standard errors and variation explanation with the final model from the exclusion and inclusion of the home variable.

4. Zero conditional mean

Keeping the home team variable in the model had a lot to do with the problem of a very conditional mean bias. It is safe to assume that fans typically don’t go to games based on the size of a venue, but rather a big portion of choosing to go to a game is dependent on which teams are playing.
Although a considerable amount of the attendance variation is explained by the model, there are parts that are omitted from the model that could prove crucial in explaining more of the variation.

There is reason to believe that there are still omitted variables that should be included in the model. These variables include, demographic for each team, number of world class players, etc. As for now the model to explain attendance has a small amount of omitted variable bias, but there is still bias. Even with all the variables implemented in the model there is still 19% of the variation in attendance not explained, leaving omitted variable bias as an option for the missing variation explanation.

I will be using a difference in difference technique to identify if there was any significant effect the FIFA Women’s World Cup and ESPN broadcasting agreement with the NWSL had on the league’s regular season attendance. This technique is used to study the effects a treatment or event has on a treatment group compared to a control group. The model can be used over two or more time periods. The difference in difference method is used to examine the FIFA and ESPN agreement as one event and how it affected a treatment group (2019 season) compared to the 2018 season. In the case of this paper’s model, the difference in difference statistical technique will use the treatment or event variable as any date after July 7th.

To understand what variables explain variations in NWSL attendance, I created multiple models to test and build upon. Every model will use attendance as the dependent variable. The first naïve model included stadiums capacities. Small stadiums were used as the omitted variable in the model.

\[
\ln(\text{Attendance}) = \beta_0 + \beta_1(\text{med\_cap}) + \beta_2(\text{large\_cap}) + u
\]
From this model, a 21.5% variation in attendance was able to be explained by the venue capacities within the league. I found that each variable in the model was shown to be statistically significant with a 99% confidence interval. This small model explains that the venue capacity could provide vital explanations as to how attendance fluctuates between different venues throughout the season.

After a venue sizes were examined, a binary variable called Weekend was created to include Friday through Sunday as ones and Monday through Thursday as zeros signifying weekdays. Much like the weekend dummy variable from Li, et al. (2019) essay, this variable was created to help explain variation in attendance depending on the time of week games were held. The home variable was used to keep track of how attendance changed depending on which team is the home team. Although the home team and venue capacity variables may seem redundant, the teams Seattle Reign, Sky Blue, and Washington Spirit all played on more than one venue as the home team and their venues varied in capacity categories. From Table 4 it is easy to see a large increase in the standard error for the large cap variable. As explained from the third assumption of multicollinearity, this jump in the standard error was anticipated due to frequent comparisons for home teams and their venue capacity. Most of the teams in the large capacity category don’t change venues or capacity sizes in the 2018 and 2019 seasons.

\[
\ln(\text{Attendance}) = \beta_0 + \beta_1(\text{med\_cap}) + \beta_2(\text{large\_cap}) + \beta_3(\text{weekend}) + \beta_4(\text{Home}) + u
\]
Table 4 shows a positive trend with each increase in the size of venue bringing in more attendance for a game. The table also shows that the increase in attendance increases with each next larger sized venue. The table also shows that the comparison between games being held on weekend and weekdays are statistically different from each other. Meaning, that there would be an expected change in attendance of it was played on the weekend compared to a weekday.

Once a naïve model was created, the difference in difference technique was used to identify if there was any significant effect the FIFA Women’s World Cup and ESPN broadcasting agreement with the NWSL had on the league’s regular season attendance. This technique is used to study the effects a treatment or event has on a treatment group compared to a control group. The model can be used over two or more time periods. The difference in difference method is used to examine the FIFA and ESPN agreement as one event and how it affected a treatment group (2019 season) compared to the 2018 season. In the case of this paper’s model, the difference in difference statistical technique will use the treatment or event variable as any date
after July 7\textsuperscript{th}. This variable is set as a binary dummy variable with the dates after July 7\textsuperscript{th} being ones, referring to as post announcement and the zeros being the dates before July 7\textsuperscript{th}. The date July 7\textsuperscript{th} was used as the post announcement because although the ESPN agreement was announced on July 4\textsuperscript{th} the World Cup was not over until July 7\textsuperscript{th}. After the announcement term was generated, the variable for the 2019 season was designed. Very similar to the treatment term, the 2019 season variable is a binary dummy variable with ones indicating the 2019 season and zeros indicating the 2018 season. The last variable used in the model is the interaction term from the treatment and 2019 season variables. The interaction variable is going to be used measure the difference in comparisons between the 2018 and 2019 season after the treatment date. The new variables were implemented into the naïve model, shown below.

\[
\ln(\text{Attendance}) = \beta_0 + \beta_1(\text{med\_cap}) + \beta_2(\text{large\_cap}) + \beta_3(\text{i\_week\_day}) + \beta_4(\text{Home}) \\
+ \beta_5(\text{treatment}) + \beta_6(\text{2019}) + \beta_7(\text{treatment \ast 2019}) + u
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Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

4. Results

Table 5 helps to explain the effects the FIFA Women’s World Cup and ESPN broadcasting agreement with the NWSL had on the league’s 2019 regular season attendance. The models four and five from Table 5 show that the variables for post July 7th and 2019 regular season have no statistical significance. This indicates that the percent change in attendance past July 7th in the season of 2018 and the percent change in attendance in the 2019 season compared to the percent of attendance in 2018 regular season don’t significantly change. The difference in difference interaction term shows a statistical significance up to the 99% confidence interval. The term explains when the 2019 regular season attendance after July 7th is compared to the 2018 regular season attendance after July 7th there are statistically significant changes in the percent of attendance in both seasons, after the FIFA Women’s World Cup and the ESPN and NWSL
broadcast agreement. The 2019 regular season after July 7th is shown to have a positive difference in attendance compared to the 2018 regular season after July 7th.

Although the difference in difference variables from model three in Table 5 explains less than 10% of the variation in attendance, it proves to be statistically significant on both the fourth and fifth model. This indicates that the difference in difference technique can hold its significant impact on attendance even with more variables to explain the attendance variation. From fourth model in the table it’s obvious to see that the addition of the difference in difference statistical technique improved the variation of attendance explained and lowered the standard errors for each variable. This explains that with more relevant variables to explain the variation in attendance less of the multicollinearity from the home team and venue capacity variables effect the more explained models. It’s also important to notice that the effects on attendance from games being played on the weekend compared to weekdays from Tables 4 and 5 are still statistically significant. This indicates that the days games are played or surely affect the attendance.

5. Conclusion

The analysis of this essay was found that, the FIFA Women’s World Cup and ESPN broadcasting agreement with the NWSL had a positive effect on NWSL regular season attendance. Games played on the weekend compared to the weekdays were also found to have a positive impact on attendance as well as increasing the venue size that the games are played at. These findings propose that NWSL teams should look to increase their venue size. The finding also suggests that the NWSL should attempt to incorporate more events during future seasons, keep striving for more television agreements with distinguished broadcasters, and work to
schedule games on more weekends during the season in order to boost attendance and further promote the league, and keep the NWSL thriving in the coming years.

Although much of the variation in regular season attendance has been explained by the model, I would like to conduct more analyses to examine if the number of world class players on a game roster affects the attendance. This could help to understand if the difference in difference technique explains that fans are excited to watch star players coming back from world events or if fans are interested in the NWSL after watching more public women’s soccer events, not just star players. An article written by Li, et al. (2019) examined this assumption for the Chinese soccer league. They found that attendance rose from rivalries and star international players presence in the game. After asking multiple sources, including NWSL, I concurred that the league doesn’t have a significant amount of rivalries to include in the mode without risking much of my degrees of freedom. The ability to measure star players effect on attendance will be possible with more data.

I would also like to include data on the number of viewers with NWSL matches over season to see if the attendance at games is affected by streaming services offered for NWSL matches. Given one of the determinants of demand from economics substitutes and compliments, It would be interesting to see if streaming services were substitutes or compliments on NWSL game attendance. Further analyses on attendance impacts from world soccer events, quality streaming deals, game scheduling, venue sizes, and star power could asses the NWSL and other leagues on increasing their attendance and creating a larger fan base.
6. References


