Does the WNBA Pay Its Players Fairly? Evidence in the WNBA Talent Market

Yang Wu

Department of Economics

Kenyon College

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Abstract

The gender pay gap in professional sports is a subject of contentious debates. Recently, female athletes have taken steps forward to oppose the pay gap, which they view as an act of exploitation by the governing and administrative bodies. To date, little research effort has been made to systematically investigate the issue of fair pay in professional women's sports. This paper applies the marginal revenue product theory to the study of player compensation in the Women's National Basketball Association (WNBA), analyzing its talent market in terms of economic efficiency. The results suggest that WNBA star players and starters are generally paid according to their respective levels of productivity, although there is evidence that inefficiencies exist with regards to rookie compensation. Specifically, I find that WNBA rookies are generally overpaid given their on-court production.

1 Introduction

Since the second half of the 20th century, women's labor force participation has increased significantly. On average, women are working longer hours and achieving higher educational attainment than ever before.[1] Despite this progress in labor force participation and educational attainment, persistent wage gaps continue to exist between women and men. How persistent is it? According to the Institute for Women's Policy Research (IWPR), the women-to-men earnings ratio for the same week of work was estimated to be 0.642 in 1980. Although this ratio had risen to 0.805 in 2016, only about 41.2% of this gain occurred between the twenty-eight year period between 1988 to 2016.[2] In fact, according to the Census Bureau, the 1.1 percent year-over-year increase in 2016 was the first time the female-to-male earnings ratio had experience an annual increase since 2007.[3]

Not only is the gender pay gap persistent through time, the issue is also widespread across various industries. New data show that while some industries have more or less achieved parity of earnings between women and men, the issue of equitable compensation continues to plague the largest industries of the economy. Based on data in 2021, the *controlled* women-to-men earnings ratios indicate that women earn, on average, 96 cents for every dollar earned by men in transportation and warehousing.[4] The same trend exists in finance, insurance, retail, and food services, where the controlled women-to-men earnings ratios have been hovering around 0.97 since 2017.[5] Simply put, despite being equally productive workers, women are consistently paid lower than men in these industries. Even in the professional sports industry, which receives ample media coverage, the issue of equitable compensation has been rampant and change has been slow-to-come.

As a case in point, tennis player Billie Jean Kong first brought awareness to the issue of fair pay in sports as early as the 1970s, when she was awarded $2,900 less than her male counterpart at the Italian Open for the same game. In 2018, Forbes released the list of the top 100 highest-paid athletes, none of whom were female athletes. Similarly, in 2017, only tennis player Serena Williams joined the list at No.56. Many believe that the events that finally brought the sports world to confront the issue of fair pay were the 2019 women's world cup games, where the U.S. women's soccer team took a highly publicized stance against inequitable pay in women's sports. In the professional sports, however, the issue of equitable compensation is nonetheless complicated by a number of factors. For one, assuming female and male athletes receive equal salary, the top male athletes still may earn more due to sponsorship and endorsement deals; research has shown that sponsors are more attracted by male athletes due to greater marketability.[6] Another factor is that, generally speaking, female athletes do not have the same level of athletic performance as male athletes.[7] To the extent that better performance

[1] https://www.npr.org/2019/06/20/734408574/new-report-says-college-educated-women-will-soon-make-up-majority-of-u-s-labor-f#:~:text=Women

[2] https://bigthink.com/robby-berman/the-frustratingly-persistent-united-states-pay-gap

[3] https://www.census.gov/library/publications/2017/demo/p60-259.html

[4] The controlled ratio, which controls for job title, years of experience, education, industry, location and other compensable factors, measures equal pay for equal work.

[5] https://www.payscale.com/data/gender-pay-gap#section02

[6] https://www.playthegame.org/news/news-articles/2011/sports-sponsors-overwhelmingly-favour-men-over-women/

[7] The current world records in sports, for instance, are predominantly held by male athletes.

leads to greater fan interest, women's sports are generally disadvantaged in this respect. The last factor is one of economics— lower attendance in women's sports relative to men's sports indicate that women's sports, on average, generate less revenue. The difference in marketability of women and men in sports thus affects their corresponding earnings.

These factors provide sufficient justification for an economic discussion of the issue of fair pay, particularly in the sports industry. A major drawback in today's discussions pertaining to the issue of fair pay is that it is often scrutinized as a political issue. *It is.* But framing the issue as entirely political omits the fact that it is also economic. While the arms of normative economics wrestle with the question of fairness, positive economics is concerned with the description, quantification and explanation of economic issues. This paper adds to the current discourse regarding fair pay by examining the talent market of the Women's National Basketball Association (henceforth, the WNBA) as a case study. Framing the issue of equitable compensation as a study of economic efficiency, I focus my analysis primarily on entertaining the "what is" question. Is there an inefficiency in the labor market for the WNBA players in terms of player pay?

2 Literature Review

Pay in professional sports has garnered a wealth of attention in the literature, with analyses focusing on various major sports leagues such as the NFL, NBA, and MLB. Evidence from the empirical works suggests that, while professional sports leagues have at their disposal a plethora of information on individual and firm level performance that is unparalleled in most industries, inefficiency continues to exist in the market for playing talent.

Inefficiency in the labor markets of professional sports was first uncovered by Scully (1974), who found that the baseball labor market under the reserve clause was anti-competitive due to the existence of monopsony power. Staying with the MLB, Hakes and Sauer (2006) finds evidence consistent with the Moneyball (2003) hypothesis that the labor market for baseball has historically undervalued on-base percentage. In the NBA, Kahn and Sherer (1988) finds substantial pay discrimination against black athletes in a league that was, at the time, 75% black. Furthermore, empirical studies such as Staw and Hoang (1995) and Camerer and Weber (1999) show that NBA draft positions unduly impact playing time and remain a significant determinant even two years into a player's career, suggesting that scouts and decision-makers are inefficient in how they assess and employ talent. With regards to the NFL, Keefer (2013), Kahn (1992), and Mogull (1981) consistently find that white players are paid a wage premium. Massey and Thaler (2006) finds that the assessment of top NFL draft picks are overvalued in a manner that is inconsistent with efficient markets.

Very few studies to date that I am aware of explore the issue of inefficiency in the WNBA. Data on the WNBA, particularly at the firm level, is scant compared to that on the NBA and like other young sports leagues, the WNBA has experienced the typical growing pains, struggling for relevance in the landscape of professional sports and in the annals of academic research. As the WNBA marks its 25^{th} season, it represents a relatively untapped resource for potential contributions to economic analysis. This paper examines the issue of equitable pay in the WNBA in an attempt to broaden the literature on the efficiency of labor markets in professional sports.

The remainder of this article is organized as follows. Section 3 provides the background on the institutional characteristics of the WNBA and its labor market. Section 4 sets up the theoretical framework that will be utilized, proposing the usage of the marginal revenue product theory to study the outcome of the WNBA talent market. Next, section 5 and 6 take on the goal of actually estimating the marginal revenue product, presenting and discussing the results of these estimations. Finally, section 7 uses the results from the previous sections to address the central premise of this paper. Section 8 concludes with a discussion of the main findings and the important lessons.

3 Background On the WNBA

3.1 League Revenue

On the heels of a highly-publicized gold medal run by the 1996 USA Basketball Women's National Team at the 1996 Summer Olympic Games, the WNBA originated with 8 teams. Today, through a sequence of expansions, contractions, and relocations, the league currently consists of 12 teams. Due to the lack of viewership, the WNBA has sustained a long period of losses, typically projected at around $10 million annually since its inception in 1996. Despite this lack of success, the league's financial status began to show some signs of improvement entering into its 15th year of operation. In December 2010, Donna Orender, former president of the WNBA, announced that the league had its first-ever "cash flow positive" team during the 2010 season. In 2013, six of the league's 12 teams reported a profit. Just exactly how financially successful the WNBA is today is not well known. On occasion, but not routinely, revenue estimates for the WNBA have been published which provides part of the picture of profitability in the WNBA. Table 1 presents some WNBA revenue estimates for the 2014 season.[8]

Table 1: 2014 WNBA Revenue Estimates

Source of Revenue		Revenue
Television Revenue		$12,000,000
Average Attendance	$7,578	
Average Ticket Price	$15	
Gate Revenue per game	$113,670	
Total Gate Revenue for 204 Regular Season Games		$23,188,680
Total Revenue		$35,188,680

Table 1 may be viewed in conjunction with Table 2, which tabulates the average salary[9] for the 2014 WNBA

[8] These estimates are based on Harris and Berri (2016).

[9] These estimates are gleaned from the Dallas Morning News. Retrieved from http://www.pressreader.com/usa/

season. Based on these estimated figures, WNBA players were paid approximately 33% of total league revenue in the 2014 season. As a comparison, it is reported that the NBA invested approximately 50% of total league revenue in player salaries in the same year. This anecdotal evidence suggests that it might be useful to study the market for player talent in the WNBA to better understand the nature of the discrepancies between the WNBA and NBA. Another noteworthy feature of the WNBA is that the league receives *some* level of financial backing from the NBA. An argument could be made here that, without this subsidy, the WNBA would have gone the way of other women's leagues with noble aspirations but little support to keep them alive.

Table 2: 2014 WNBA Payroll

Salary	
Average Salary	$75,000
Number of Players	154
Total Payroll	$11,550,000
Payroll as Percent of Total Revenue	32.82%

3.2 Collective Bargaining Agreement

The labor market for WNBA players is regulated under the collective bargaining agreement (henceforth, the CBA), of which the negotiation takes place every four years between the WNBA and the WNBA Players Association (WNBPA). The CBA clearly delineates between two common types of contracts— rookie contracts and standard contracts. Under the most recent CBA, any player who has not previously signed a contract to play in the WNBA is eligible to sign a rookie contract. Table 3 illustrates the terms for 2020 rookie contracts.

Table 3: 2020 Rookie Scale

Pick	2020	2021	2022	2023(Tm Option)
Picks 1-4	$68,000	$69,360	$76,297	$86,701
Picks 5-8	$65,250	$66,555	$73,211	$83,194
Picks 9-12	$62,500	$63,751	$70,127	$79,690
Second Round	$59,750	$60,946	$67,042	$76,183
Third Round	$57,000	$58,141	$61,049	$69,770
Undrafted	$57,000	$58,141		

The base salaries listed, that is, salary without any bonuses, and the lengths of rookie contracts are fully specified for each draft pick, meaning there is little to no room for negotiation between the player and the team. This is notably different from the NBA, where players can sign for as much as 120% of the rookie scale.[10]

the-dallas-morning-news/20150726/282364038377418/TextView

[10] https://www.hoopsrumors.com/2020/11/rookie-scale-salaries-for-2020-nba-first-round-picks.html

Moreover, rookie base salaries are not guaranteed ("protected," in the language of the CBA); therefore, players are only paid for the portion of the season they are actually on the roster. This is in stark contrast to the NBA, whose rookie scale contracts are guaranteed for the first two years, even for some second round draftees.

When it comes to standard contracts, the CBA specifies a salary cap and a salary floor, with one key distinction with regards to free agency. The WNBA is different from most other professional sports leagues in the US in that the salary cap is a hard cap with very little wiggle room. On the other hand, teams may be below the minimum team salary before the season and throughout the season with no penalty. Moreover, each team is allowed to designate no more than one player as a "core" player (using the language of the CBA) by extending a core qualifying offer. The terms of the core qualifying offer are a fully guaranteed, one-year contract with a base salary equal to the supermax, which allows teams to pay up to 16.5% of the salary cap. In contrast, the "Designated Veteran Player Extension" rule in the NBA allows teams to sign qualified "star" players to maximum five-year contracts worth up to 35% of the salary cap with 8% escalation in each subsequent year. Unlike the core contracts in the WNBA, the super-max rule in the NBA does not restrict a team's ability to sign multiple *star* players. One of the goals in this paper is to study the outcomes of the WNBA talent market under these institutional characteristics.

But before I proceed with the main objective of this paper— that is, I wish to investigate if there is an inefficiency in the labor market for WNBA players— I must establish the theoretical framework with which the issue of equitable compensation must be considered.

4 Theoretical Framework

4.1 The Marginal Revenue Product

In the professional sports industry, fans are the consumers of the end product while teams are the firms who employ the factors of production— crudely speaking, playing and coaching talent— in effort to meet the demand for sports. It is argued that teams in sports leagues are primarily engaged in the production of wins, which is commonly proxied by winning percentage in empirical studies (see Davis and End (2009) for the NFL, Chatterjee, Campbell, and Wiseman (1994) for the NBA, Schwartz and Zarrow (2009) for the MLB). Theory posits that payments to factors of production, such as players, should be determined by their marginal revenue product, or MRP:

$$MRP(W) = MP(W) \times MR(W) \tag{1}$$

In equation 1, W is team winning percentage. MP(W) is the marginal player product, which is essentially the player's the contribution to winning. MR(W) is the marginal revenue of winning. Equation 1 allows us to apply the theory of marginal revenue product to the issue of equitable compensation in the WNBA. In an efficient talent market, one would expect that WNBA players are paid close to their MRP. Therefore, to address the main objective of this paper, I must compare the WNBA players' salaries to their MRP. *Large* differences in WNBA salaries relative to the players' MRP (irrespective of the direction) will be construed as evidence of inefficiency in the WNBA talent market.

4.2 A Two-part Model

Following the approach devised by Scully (1974), the task of estimating MRP will involve separately estimating two regression models. The underlying logic of the methodology is as follows: playing performance contribute to wins, and wins are, in turn, sold to fans. While the MRP cannot be modeled directly, the contribution of player performance to team winning and that of team winning to team revenue can be modeled separately to obtain estimates of the two components of MRP— marginal product (MP) and marginal revenue (MR). Therefore, a simple two-part model for estimating the MRP is given by the following system.

$$\text{Team Winning} = f(\text{Player Performance, Disturbances}) \tag{2}$$

where team winning is defined as a function of player performance and disturbances, the factors that influence winning which are not associated with player performance, such as coaching, team chemistry, or simply chance. By relating team winning to player performance, equation 2 allows for a straightforward way to estimate marginal product. If teams are engaged in the business of producing wins, then the players' contribution to wins is their marginal product. Furthermore, the marginal revenue is given by:

$$\text{Team Revenue} = f(\text{Team Winning, Other Factors}) \tag{3}$$

where team revenue is assumed to hold a functional relation with team winning and other control factors related to revenue. In equation 3, the isolated effect of team winning on team revenue will be interpreted as marginal revenue. That is, marginal revenue is the additional revenue generated by additional winning.

5 Marginal Product

5.1 Data and Model

To model player productivity, I need a measure of player performance. Empirical works in basketball have traditionally used the official NBA performance metric, called the NBA Efficiency Rating, which is essentially computed by adding the positive statistics (points, rebounds, steals, assists, and blocked shots) and subtracting the negative statistics (turnovers and missed shots). A similar metric exists for the WNBA. However, as Berri (2008) argues, this methodology ignores the differing impact that each statistic has on winning. This drawback of the WNBA Efficiency metric leads me to employ a measure detailed in Berri (1999), Berri and Krautmann (2006), Berri, Schmidt, and Brook (2006), and Berri (2008). The Wins-Produced model is grounded in the theory that basketball is a game of possessions; moreover, winning in basketball is a function of a team's offensive and defensive efficiencies. Berri (1999) defines efficiency as the amount of points scored or surrendered per possession. The model then relates the number of wins to the offensive and defensive efficiency metrics:

$$\text{Wins} = \frac{\text{Points Scored}}{\text{PE}} + \frac{\text{Points Surrendered}}{\text{PA}} + \varepsilon \tag{4}$$

where[11]

- $\text{PE} = \text{FGA} - \text{REBO} + \text{TO} + 0.0527 \cdot \text{FTA}$
- $\text{PA} = \text{DFGM} + \text{DTO} + \text{TO} + 0.0527 \cdot \text{DFTM} + \text{REBTM}$

This model is fitted using panel data comprising of 16 WNBA franchises from 2000 to 2019. The sample is unbalanced. Five teams— the Detroit Shock, the Orlando Miracle, the Utah Starzz, the Tulsa Shock, and the San Antonio Stars— relocated to different cities during this period. Moreover, this twenty-year period saw six teams— the Charlotte Sting, the Cleveland Rockers, the Houston Comets, the Miami Sol, the Portland Fire, and the Sacramento Monarchs— fold due to their inability to find new owners. To the extent that units composing the panel exit and enter into the panel due to systematic, unobserved characteristics, attrition bias may be present in the results. It can be argued that exits and entries due to re-locations are random in nature. In any given season, teams may relocate to other cities due to a variety of reasons that do not have to be systematic. However, exits of observational units due to teams folding may be systematic— for instance, they may have all held losing records. If this is true, then such exits of panel units are not random and will likely cause bias. To investigate, I examine the winning percentages of folded teams in the season prior to their exits. Table 4 summarizes the results of the investigation.

Table 4: Team Winning Percentage Prior to Exits

Team	Season	Winning Percentage
Charlotte Sting	2006	0.3235
Cleveland Rockets*	2003	0.5294
Houston Comets*	2008	0.50
Miami Sol*	2002	0.4063
Portland Fire	2002	0.3125
Sacramental Monarchs	2009	0.3529

Note: * indicates playoff appearance

As can be seen, although most of the teams recorded below-average (.500 record) winning percentages, three of the six teams actually made the playoffs prior to their exits, indicating attrition bias is not a substantial cause for concern.

5.2 Results

Table 5 presents the regression results for the model given by equation 4. As can be seen, the offensive and defensive efficiency measures explain approximately 58% of the variations in wins. Both offensive and defensive

[11] Definitions for these abbreviated variables are given in Table 6

efficiency metrics are statistically significant at the 1% significance level and have the correct signs.

Table 5: Wins-Produced Model

	Wins
$\frac{\text{Points Scored}}{\text{PE}}$	62.591***
	(4.439)
$\frac{\text{Points Scored}}{\text{PA}}$	−80.704***
	(5.732)
Observations	262
R^2	0.583
Adjusted R^2	0.580
Note:	*p<0.1; **p<0.05; ***p<0.01

Following the approach of Berri (1999), I can now ascertain the marginal value of all the individual elements of the offensive and defensive efficiency metrics (points, offensive rebound, steals, turnovers, etc.). Table 6 presents the marginal values of each statistic.

Table 6: The Impact of Various Statistics on Winning in the WNBA

Player Variables	Marginal Value
Points Scored (PTS)	0.024
Field Goal Attempt (FGA)	−0.023
Free throw Attempt (FTA)	0.012
Offensive Rebounds (REBO)	0.023
Defensive Rebounds (REBD)	0.017
Steal (STL)	0.017
Turnover (TO)	−0.023

Team Variables	Marginal Value
Points Surrendered (DPTS)	−0.024
Opponent's Field Goals Made (DFGM)	0.017
Opponent's Free Throws Made (DFTM)	0.009
Opponent's Unforced Turnovers (DTO - STL)	0.017
Team Turnover (TOTM)	0.017
Team Rebounds (RBTM)	0.017

Given the marginal values from Table 6, marginal product is then given by the following equation:

$$\begin{aligned}\text{MP} = \text{Wins Produced} = [\,&0.024 \cdot \text{PTS}_{adj} - 0.023 \cdot \text{FGA}_{adj} + 0.012 \cdot \text{FTA}_{adj} + 0.023 \cdot \text{REBO}_{adj} \\ &- 0.023 \cdot \text{TO}_{adj} + 0.017 \cdot \text{REBD}_{adj} + 0.017 \cdot \text{STL}_{adj} - 0.024 \cdot \text{DPTS}_{adj} \\ &+ 0.017 \cdot \text{DFGM}_{adj} + 0.009 \cdot \text{DFTM}_{adj} + 0.017 \cdot \text{DTO-STL}_{adj} \\ &+ 0.017 \cdot \text{RBTM}_{adj} + 0.017 \cdot \text{TOTM}_{adj} + \text{Constant}\,] \times 40\end{aligned}$$

where

- Statistic_{adj} is a player's season total divided by the number of minutes played that season
- multiplying by 40 provides the a wins produced per 40 minutes

Next, Table 7 summarizes the top ten most productive players in the WNBA for the 2019 season. Notably, all but two players— Mercedes Russell and Dearica Hamby— have been an all star at some point in their careers. Nneka Ogwumike and Sylvia Fowles were respective league MVP's for the 2016 and 2017 seasons. Elena Delle Donne won two MVP trophies in 2015 with the Chicago Sky and again in 2019 with the Washington Mystics. The last column in Table 7 displays player rankings in terms of the WNBA efficiency metric. As can be seen, six of the top ten win-producers in 2019 also ranked top ten in terms of their efficiency ratings. Given these results, it appears that the method for estimating marginal product is at least not exceedingly erroneous. That is, we expect to see star players dominate the list, and Table 7 provides some confidence that the method is not spurious. However, since I need to use these estimates of marginal product, I must also assess the accuracy of the method.

Table 7: Top Ten Wins Producers (2019)

Player	Team	Wins-Produced	Rank	WNBA Efficiency Rating Rank
Elena Delle Donne	WAS	6.6327	1	1
Nneka Ogwumike	LAS	6.3255	2	4
Sylvia Fowles	MIN	6.0768	3	11
Jonquel Jones	CON	5.5592	4	7
Natasha Howard	SEA	4.9614	5	8
Dearica Hamby	LVA	4.9485	6	22
Liz Cambage	LVA	4.8720	7	6
Brittney Griner	PHO	4.6463	8	3
Napheesa Collier	MIN	4.4313	9	23
Mercedes Russell	SEA	4.1832	10	28

5.3 Robustness Test

Does the method accurately depict a player's *contribution to winning*? In order to answer this question, the estimated marginal product of each player is summed across each team for the 2019 WNBA season. The summation is interpreted as the number of predicted wins, which are then compared to the actual wins for each team in 2019. The results are reported in Table 8.

Table 8: Predicted Wins Versus Actual Wins (2019)

Team	Wins (Actual)	Wins (Predicted)	Error
Atlanta Dream	8	2	6
Chicago Sky*	20	18	2
Connecticut Sun*	23	11	12
Dallas Wings	10	13	−3
Indiana Fever	13	5	8
Las Vegas Aces*	21	19	2
Los Angeles Spark	22	15	7
Minnesota Lynx*	18	12	6
New York Liberty	10	12	−2
Phoenix Mercury*	15	12	3
Seattle Storm*	18	16	2
Washington Mystic	26	21	5

Note: * indicates playoff appearance

As can bee seen from Table 8, the accuracy of the methodology is mixed, with some accurate but also some inaccurate predictions. Of the twelve teams under examination, the average difference between predicted and actual wins is 4.7699. In addition, both over- and under estimations are present, making it difficult to say conclusively that the true direction of any potential bias is one way or the other. Still, the errors are overwhelmingly positive, and so the marginal product for each player may be interpreted as a lower bound estimate. A potential cause of these inaccuracies may lay in Table 5. One possible explanation is that offensive and defensive efficiency metrics explain only 58% of the variations in team wins. Berri (1999) reports that the variation in wins is reduced by 94.6% when the two efficiency metrics are included in the model. Apparently, for the WNBA, there remains a great deal of unexplained variation in team wins, even after controlling for a team's offensive and defensive efficiency metrics. An observation from Table 8 is that there is a difference in terms of accuracy, particular between playoff and non-playoff teams. The average error is 5.1667 for non-playoff teams compared to 4.5 for play-off teams. Assuming that play-off teams tend to have better players, it may be that marginal product estimates for the top players are more accurate than those for the average player.

Before turning to marginal revenue, to rule out the possibility that an inadequate model is causing biased or inefficient coefficients, tests for normality and non-constancy of error variance are conducted. The score test for non-constant error variance ($p = 0.57086$) and the Breusch-Pagan test ($p = 0.09382$) both indicate that homoscedasticity is present at the 5% significance level, and so the estimated coefficients are efficient. The Pearson chi-square normality test ($p = 0.03629$) reveals that there may be slight non-normality. However, with a large sample size ($N = 262$), the sampling distributions of the parameter estimators will have the property of asymptotic normality and the estimators will remain BLUE. Moreover, the Box-Cox procedure suggests $\lambda = 0.934$, which is essentially a power transformation of 1, that is, no transformation. Given that the explanatory power of the offensive and defensive efficiency metrics on team winning has been shown to be consistently high in Berri (1999), Berri and Krautmann (2006), Berri, Schmidt, and Brook (2006), and Berri (2008), any omitted variable bias is unlikely to be caused by the methodology used. There seems to be something that causes the model to make accurate predictions in some teams but inaccurate predictions in others. Further investigation and diagnostics will be needed to address this issue. For the purpose of this paper, however, we will proceed to estimate the next component of the MRP.

6 Marginal Revenue

Following the approach of Scully (1974), I next want to estimate the marginal effect of winning on revenue, which I will interpret as the marginal revenue of winning. This methodology requires team-level revenue data over time. As mentioned in section 3.1, there is currently no comprehensive revenue data for the WNBA. To bypass this limitation, the regression model is fitted using data from the NBA and an estimated marginal revenue is obtained from the regression coefficient. Assuming that the WNBA league revenue is simply a fraction of the NBA league revenue, I then scale the estimated marginal revenue for the NBA by the following ratio

$$\frac{\text{Revenue Per WNBA Game}}{\text{Revenue Per NBA Game}} \tag{5}$$

to obtain a guesstimate of the WNBA's marginal revenue of winning. In 2018, it was estimated that the WNBA generated \$60 million in total revenue to the NBA's \$7.4 billion.[12] Controlling for season lengths, equation 5 can be computed as follows:

$$\frac{60,000,000}{34} \div \frac{7,600,000,000}{81} \approx 0.01881 \tag{6}$$

From equation 6, it follows that an estimate of the WNBA's marginal revenue of winning is given by:

$$MR_{WNBA} = 0.01881 \cdot MR_{NBA} \tag{7}$$

6.1 Data and Model

To estimate the WNBA's marginal revenue of winning, I construct a comprehensive dataset that covers the period from 1990 to 2019. The sample contains 789 team-seasons. Due to expansion and contraction in professional sports leagues, the panel is unbalanced, with units exiting and entering the sample throughout the thirty-year period. A few notes about this data set:

[12] https://www.wsn.com/nba/nba-vs-wnba/

- Two Canadian teams— the Vancouver Grizzlies and the Toronto Raptors— are dropped from the sample due to unavailable market size data
- Team revenue data for the 1996-1997 NBA season is unavailable, likely due to the 1996 NBA lockout
- The Charlotte Hornets, the Seattle Supersonics, and the Nersey Nets each relocated to a different city at some point over the thirty year period being studied
- The only expansion that involved a "new" team is Michael Jordan's Charlotte Bobcats, which joined the league in 2004, after the original Charlotte Hornets team had moved to New Orleans

From the literature, I identify a list of explanatory variables that are most commonly used in revenue regressions. Consistent with Scully (1974), my primary variable of interest is team win percentage. The methodology from section 4.2 requires that the coefficient on win percentage (WINPCT) be positive. Next, the statistical relation between team revenue and market size has been empirically tested; I include two variables— metropolitan statistical area population (POP) and per capita income (PCINC)— to control for the impact of market size on team revenue. Treber, Mulcahy, and Sharma (2016) finds that performance in the previous season has a significant influence on team revenue in the current season. This is because season tickets are usually sold at the start of the season and ticket sales make up a significant portion of team revenue. To control for previous season performance, I include a variable equaling the number of play-off games played by a team in the previous season (POG). I expect my results to be consistent with their conjecture. Moreover, Bradbury (2018) uses a variable to control for stadium capacity (STDCAP). I anticipate that larger stadiums would have a positive impact on team revenue. Variable definitions and their respective units are organized in Table 9 for reference.

Table 9: Variable Definitions

Variable Name	Variable Definition
REV	Total revenue, in millions of U.S. dollars, generated by team i in season t
WINPCT	Winning percentage, scaled from 1-100, of team i in season t
POG	Number of play-off games played in the previous season by team i in season t
STDCAP	Stadium capacity, in thousands, of team i in season t
POP	Total population, in millions, of MSA in which team i is located in season t
PCINC	Per capita income, in thousands of U.S. dollars, of MSA in which team i is located in season t

Consistent with Scully (1974), a linear specification is used in addition to the natural logarithm specification (henceforth, log-model) for the revenue regression. Scully (1974) argues that, for computational simplicity, a linear specification (henceforth, level-model) in the dependent variable as well as in the parameter of interest may be desired. For team i in year t, the regression model is then given by:

$$\vec{Y} = \mathbf{X}\vec{\beta} + \vec{\varepsilon} \tag{8}$$

where

- $\vec{Y}$ is a vector of revenues or natural logarithm of revenues for team i in season t
- $\mathbf{X}$ is the design matrix with a column of 1s as well as columns of win percentages, number of play-off games played in the previous season, stadium capacity, natural log of MSA population, and natural log of MSA per capita income for team i in season t
- $\vec{\beta}$ is a 7×1 vector of model parameters to be estimated
- $\vec{\varepsilon}$ is the vector of random errors

The data used to fit this model come from various sources. NBA team revenue data are obtained from Rodney Fort's Sports Business Data. NBA team variables are constructed using statistics from basketball reference.com. Stadium data are gleaned from various sources including venue websites, Wikipedia pages, and news articles. Market size variables are built using data taken from the Bureau of Labor Statistics. Table 10 reports the summary statistics of the variables defined in Table 9.

Table 10: Summary Statistics

Statistic	Max	Mean	Median	Min	25^{th}Percentile	75^{th}Percentile	St. Dev.
REV	472	118.901	102	22	66.4	150	75.278
WINPCT	89.024	50.253	51.220	10.606	39.024	62.000	15.374
POG	26	5.483	4	0	0	10	6.680
STDCAP	71.000	19.360	18.798	10.000	18.306	19.812	4.525
POP	19.335	5.146	3.840	0.757	1.971	5.743	4.731
PCINC	2,963.714	42.954	38.404	16.461	29.357	46.677	104.900

6.2 Model Diagnostics

The Shapiro-Wilk normality test ($p < 2.2 \times 10^{-16}$) and the Anderson Darling test ($p < 2.2 \times 10^{-16}$) conclude that the error terms are far from normal. A Box-Cox procedure on the dependent variable suggests $\lambda = 0$, which is the natural logarithm transformation. This makes sense as the distribution of team revenues is positively skewed, and it can also be discerned from Table 10 that the mean is larger than the median. Nevertheless, given the large sample size ($N = 789$), the sampling distributions of the estimated coefficients will be asymptotically normal by the Central Limit Theorem— their distributions approach normality under very general conditions when the sample size is large. Thus, in our case, the sample size is large enough that the estimators will remain unbiased even if the probability distributions of the dependent variable, and thus the error terms, are far from normal.

Next, the Breusch-Pagan test ($p < 2.2 \times 10^{-16}$) and the score test for non-constant error variance ($p < 2.2 \times 10^{-16}$) reveal the presence of heteroskedasticity. Ervin and Long (2012) recommends the use of the "HC3" error terms variance-covariance matrix to correct for non-constant error variance, which performs consistently for sample size as small as $N = 25$. In the next section, robust standard errors computed using the HC3 estimator will be presented. Coefficients that remain statistically significant even after this boost to standard error will be considered efficient, providing confidence that the variable under examination has a significant statistical relation with the dependent variable, team revenue.

Lastly, graphical analysis reveals that there is no non-linearity issues between our variable of interest, win percentage, and the dependent variable, team revenue, both before and after the natural log transformation on team revenue.

6.3 Results

Table 11 reports the results for the regression model given by equation 8. For the log-model, the variations in the natural log of revenues is reduced by 60% when the set of explanatory variables is included in the model. For the level-model, the explanatory power of same set of variables is lower, $R^2_{adj} = 0.515$. Given that there is no non-linearity issues pertaining to our variable of interest, the R^2 values provide some confidence that at least our models are not spuriously fitted.

The model utility F-tests of joint-significance for both model specifications conclude that not all parameters are zeros. Examining the individual t-tests, the natural log of MSA per capita income is statistically significant and has the expected sign. However, the coefficient on the natural log of MSA population has the anticipated sign but is statistically not different from zero. A possible explanation here is that there is a computational relationship between population and per capita income. In other words, these two variables may contain the same information and the inclusion of one in the model essentially eliminates the need for including the other. To investigate, the variable for MSA per capita income is dropped and the regression model given by equation 8 is fitted again. For both model specifications, the coefficient on the natural log of MSA population becomes statistically significant, though the explanatory power of both models is reduced drastically— $R^2_{adj} = 0.0785$ for the log-model and $R^2_{adj} = 0.09067$ for the level-model.

At the 1% significance level, the number of play-off games played in the previous season is statistically different from zero. Consistent with the findings of Treber, Mulcahy, and Sharma (2016), there is strong evidence that a statistical relation exists between previous performance and team revenue. The effect size is economically significant for both model specifications. In the level-model, one additional play-off game played in a season is associated with a 1.217 million increase in team revenue in the next season. For the log-model, one more play-off game played in a season is approximately associated with a 1.2% increase in team revenue. For a median revenue team with 102 millions in revenue, a 1.2% increase in revenue equals 1.224 million in dollar value.

Table 11: Revenue Regression Results

	ln(REV)	REV
	(1)	(2)
WINPCT	0.004**	0.335*
	(0.00161)	(0.19)
ln(POP)	0.026	8.730
	(0.05)	(5.46)
ln(PCINC)	1.330***	140.582***
	(0.35)	(38.11)
STDCAP	0.001	−0.053
	(0.00482)	(0.34)
POG	0.012***	1.217***
	(0.00247)	(0.34)
Intercept	−0.546	−424.184***
	(1.28)	(139.54)
Observations	789	789
R^2	0.603	0.518
Adjusted R^2	0.600	0.515
Residual Std. Error (df = 783)	0.406	52.445
F Statistic (df = 5; 783)	237.557***	168.100***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

An interesting finding, however, is the negative estimated coefficient on the stadium capacity variable in the level-model. Although the coefficient is not statistically different from zero, this finding is surprising. To investigate, I look for the potential presence of multicollinearity, which will affect the variability of estimated regression coefficients and, in some instances, may even change the sign of the coefficients depending on which of the explanatory variables are included in the model. A standard VIF procedure concludes that none of the VIF values exceeds the value of 2. It is unlikely that multicollinearity is the cause of this unexpected sign change. Ultimately, this finding is inconsistent with the findings of Bradbury (2018), where a statistically significant relation is reported between stadium capacity and team revenue.

Finally, in both model specifications, there is a statistically significant linear association between win percentage and team revenue. In the level-model, a one percentage point increase in win percentage is associated with a $\$335,000$ $(0.335 \times 1,000,000)$ increase in team revenue. For the log-model, a one percentage point increase in win percentage is associated with, by approximation, a 0.3999% (0.003999×100) increase in team revenue. Again, using the median revenue in our sample (\$102 million), a 0.3999% increase in revenue is equal to $\$407,898$ in dollar values[13]. Which model specification should be used to represent marginal revenue? By strict statistical rigor, it may be that the log-model is preferred. For one, model diagnostics procedure suggests a natural log transformation on the dependent variable, and so the log-model is an improvement upon the level-model in terms of goodness-of-fit. Secondly, the estimated coefficient on win percentage in the log-model is preferred as it is statistically significant at the 5% significance level, as supposed to the 10% significance level for the level-model, even after correcting for heteroskedasticity.

Applying the ratio from equation 6 to the NBA's estimated marginal revenue of winning, we obtain:

$$\$407,898 \times 0.01881 \approx \$7673 \tag{9}$$

which is interpreted as saying that a one percentage point increase in win percentage in the WNBA generates an additional $\$7,673$ in revenue.

7 Marginal Revenue Product

The estimates of marginal product and marginal revenue from sections 5 and 6 are employed to estimate the MRP of the top ten most productive players in the 2019 season. The Wins-Produced column from Table 7 is adjusted to represent the contribution of each player in terms of win percentage— that is, how much is each player's marginal product worth in percentage points? Letting x_i be the increase in win percentage contributed by player i, the marginal revenue product of player i, denoted MRP_i, is simply computed as:

$$\text{MRP}_i = x_i \times \$7673$$

Table 12 presents the results of these calculations, including the intermediate step of adjusting the marginal product. In Scully (1974), the MRP is interpreted as a gross value, or an upper bound. The argument is that

[13]This is computed by first solving for the variable x in $0.3999 = 100 \times \frac{x-102}{102}$. Then, subtract 102 from x to obtain the estimated difference between initial and final dollar values.

there are costs related to training, transportation, and equipment that would, in reality, lower the net MRP of each player. However, as mentioned in section 5, the estimated marginal product can be interpreted as a lower bound since the errors are overwhelming positive. It is unclear whether these effects would ultimately cancel each other out and leave us with an accurate measure of net MRP. For the sake of being consistent with Scully (1974), I will describe these MRP estimates as gross values.

Table 12: Gross MRP for Top Ten Wins Producers (2019)

Player	Team	Wins-Produced	$(\frac{\text{Wins-Produced}}{34}) \times 100$	Gross MRP
Elena Delle Donne	WAS	6.6327	19.5080	$149,685
Nneka Ogwumike	LAS	6.3255	18.6045	$142,753
Sylvia Fowles	MIN	6.0768	17.8731	$137,140
Jonquel Jones	CON	5.5592	16.3506	$125,458
Natasha Howard	SEA	4.9614	14.5923	$111,966
Dearica Hamby	LVA	4.9485	14.5543	$111,675
Liz Cambage	LVA	4.8720	14.3295	$109,950
Brittney Griner	PHO	4.6463	13.6657	$104,857
Napheesa Collier	MIN	4.4313	13.0332	$100,004
Mercedes Russell	SEA	4.1832	12.3035	$94,405

7.1 Is There An Inefficiency In The WNBA Talent Market?

To address this question, I obtain an estimate of what Scully (1974) refers to as the rate of monopsonistic exploitation.

$$\text{Rate of Monopsonistic Exploitation} = \frac{\text{Gross MRP} - \text{Salary}}{\text{Gross MRP}}$$

The rate of monopsonistic exploitation takes values between 0 and 1. These rates are interpreted as the percentages of the gross marginal revenue product that is retained by the team. Thus, it follows that a value of 1 indicates complete exploitation, that is, a team retains 100 percent of the gross marginal revenue product; conversely, a value of 0 implies no exploitation— in other words, player salaries equals gross MRP. Table 13 reports the results of this investigation.

Does the WNBA talent market pay the players efficiently? Overall, the evidence is mixed. For the top three most productive players, the results seem to indicate that they were paid close to their MRP in the 2019 season. If the MRP reported in Table 12 is indeed an upper bound, it may very well be that the true rates of monopsonistic exploitation for these three players are even lower. Conversely, if the marginal product of these players are in reality higher than the lower bound estimates reported in Table 12, then the gross MRP estimates of these players may be closer to the true net MRP. Furthermore, for three players— Dearica Hamby, Liz Cambage, and Brittney Griner— the evidence suggests that they are overpaid relative to their production

Table 13: Gross MRP, Salary, and Rates of Monopsonistic Exploitation for Top Ten Wins Producers (2019)

Player	Team	Gross MRP	Salary	Rates of Monopsonistic Exploitation
Elena Delle Donne	WAS	$149,685	$115,000	0.23
Nneka Ogwumike	LAS	$142,753	$115,000	0.19
Sylvia Fowles	MIN	$137,140	$113,360	0.17
Jonquel Jones	CON	$125,458	$59,718	0.52
Natasha Howard	SEA	$111,966	$105,000	0.06
Dearica Hamby	LVA	$111,675	$115,000	−0.03
Liz Cambage	LVA	$109,950	$115,000	−0.05
Brittney Griner	PHO	$104,857	$115,000	−0.10
Napheesa Collier	MIN	$100,004	$49,539	0.50
Mercedes Russell	SEA	$94,405	$41,965	0.56

on the court. An argument can be made that inefficiencies exist in the opposite direction of what is commonly believed to be the case in the WNBA. On the other end of spectrum, three players— Mercedes Russell, Napheesa Collier, and Jonquel Jones— are moderately exploited, as they receive only about 50% of their gross MRP.

What is the story here? At first glance, it appears there is no pattern as to why some players are paid closer to their MRP than others. Yet, a closer investigation reveals that the three most exploited players— Mercedes Russell, Napheesa Collier, and Jonquel Jones— are the only players on this list who were on their rookie contracts in 2019. As mentioned in section 3.2, WNBA rookies contracts typically leave little room for negotiation. Given these constraints, inefficiencies may arise when a rookie's contribution to winning, and thus to generating additional revenues, greatly exceeds the expected cost of her service, which is uniformly specified in the CBA. But does this suggest systematic exploitation of WNBA rookies by their respective teams? Perhaps not entirely. In the WNBA talent market, the terms of rookie contracts should reflect the league's expectation of rookie performances over the course of four seasons. Some level of inefficiency is bound to exist since not all rookies are of the same quality; on the other hand, it is usually difficult to predict at the outset how well a rookie will perform professionally. The only argument that could be made here is that the lengths of rookie contracts, coupled with the fact that there is little room for negotiation, may lead to inefficiencies *in the case* when a rookie clearly outperforms her contract but is unable to renegotiate due to the CBA's constraints on rookie contracts.

7.2 Ex Post Analysis

What is the story for the other players who are not on the top 10 list? In other words, are rookies generally exploited to a larger extent compared to the star players or even the average starters, or are the three rookies identified from Table 13 simply anomalies? To investigate, I divide a sample of 141 players into three groups— rookie, starter, and star— based on their estimated marginal product. The threshold for star players will be the average number of wins produced by the top ten most productive non-rookie players in the 2019 season. Similarly, the threshold for starters will be the average number of wins produced by non-rookie starters between the 50^{th} and the 100^{th} percentiles of the distribution of marginal product. Lastly, the threshold for rookie players will be the average number of wins produced by all rookies in the sample. For each group, I compute the gross marginal product, marginal revenue product, and rate of monopsonistic exploitation. The salary thresholds will be the minimum rookie salary ($\$41,965$), the median salary ($\$57,329$) and the max salary ($\$117,500$) for the sample. The results are reported in Table 14.

Table 14: Ex Post Analysis of The WNBA Talent Market

Group	Wins-produced	GMRP	Salary	Rates of Monopsonistic Exploitation
Rookie	0.7869	$\$17,758$	$\$41,965$	-1.36
Starter	2.6957	$\$60,836$	$\$57,329$	0.06
Star	5.6342	$\$127,151$	$\$117,500$	0.07

As can be seen from Table 14, the evidence seems to suggest that star WNBA players are paid remarkably close to their gross MRP. On average, teams only retain about 7% of the gross MRP of a star player. For the average starter, the rate of monopsonistic exploitation is 6%, which, given that the gross MRP may an upper bound, does not appear to be exceedingly anti-competitive. For the 2019 season, the average starter tends to be paid 94% of her gross MRP. It is interesting, however, to find that the average rookie in the WNBA is paid extremely inefficiently and not in the direction that one would expect given the constraints on the rookie contracts discussed in section 3.2. The typical rookie's contribution to winning, 0.7869, is awfully underwhelming relative to the other two groups. This finding suggests that the three players identified from Table 13 are anomalies. According to Table 14, it can be argued that not only are teams not exploiting those who quality for rookie contracts, they are receiving negative economic rents just to keep the rookies on the team. Why do rookies, on average, perform poorly compared to the other two groups? A quick investigation reveals that rookies, on average, play a total of 11.32 minutes per game compared to the starters' 21.81 minutes and the stars' 27.59 minutes. As discussed in section 5, the marginal product estimates may be more accurate for higher quality players. Assuming that higher quality players play more minutes, this implies that the model is not reliable for players who play few minutes. But while some level of the below-average contributions are attributable to limited playing time, it remains an interesting, and perhaps, unexpected finding that the current CBA pay structure leads to such inefficiencies when it comes to rookie salaries. A possible explanation for the existence of such inefficiencies is that, somewhere down the line, unproductive rookies become productive starters or are simply out of the league (see row 1 and 2 in Table 14). Teams are always on the look-out for talented rookies to contribute to winning, but teams generally do not have the ability to predict the future and so evaluating rookies become, in essence, a game of hit-or-miss. This may be especially true for a league like the WNBA, which has struggled not only financially but also in terms of generating fan interest and finding talent.

8 Conclusion

To conclude, the main objective in this paper is to investigate whether there is an inefficiency in the WNBA talent market. On this premise, I find that the evidence is mixed. While the starters and star players are paid close to their gross MRP, there is evidence that rookies are over-paid relative to their production on the court. As for the common accusation of,"Are WNBA players being paid unfairly?", the results of my analysis suggests that no systematic exploitation of WNBA players exists. On the other hand, there is evidence that the opposite of the accusation is true— some WNBA players may be overpaid— especially those who are signed to rookie contracts.

As mentioned in section 2, another goal of this paper is to broaden the study of labor market inefficiencies by examining a seldom studied league outside of the major four. A few lessons are worth summarizing at the conclusion of my analysis. First, one of the biggest challenges throughout this paper is data limitation, and, in many instances, I have to rely on back-of-the-envelope estimations to bypass these limitations. While the reader should have confidence that the estimation methodologies employed in this paper are theoretically and empirically sound, the accuracy of these estimations will certainly improve if more data become available. As the WNBA continues to grow, it may be a worthwhile investment for the league to make more information available to the public, which will generate more research interest that may be beneficial to their product in the long term. Secondly, in section 5, an interesting finding is that the explanatory power of the Wins-Produced model, which has been shown to adequately model winning in the NBA, is significantly reduced when applied to the WNBA. A natural extension of this paper is to investigate further as to why such an empirical inconsistency exists. Is it simply that some sports translate differently than others for men and women's sports, for whatever reason?

Next, an important implication from section 3.1 is that WNBA players are paid a smaller share of total league revenue compared to the NBA. However, a study of the WNBA labor market using the framework of marginal revenue product reveals that such comparisons may be misguided. It may be that the reason why WNBA players are paid a smaller share of league revenue is simply because their MRP do not justify their being paid a larger share of league revenue, which is already significantly less than the NBA revenue. Given the findings in this paper, it may not possible to argue that the discrepancy in players' share of revenue is due to inefficiency in the WNBA talent market.

From section 3.2, it may be inferred that the contract constraints resulting from the CBA (for instance, WNBA rookies have little bargaining power and, more importantly, they do not have guaranteed pay) are more league-friendly than those in the NBA. At the conclusion of my analysis, however, the finding that rookies are generally overpaid relative to their MRP seems to go against this surmise. How do we reconcile this? I argue that contract constraints resulting from the CBA could reflect monopsony power by the league, or they could represent the shared acknowledgement between both sides that more flexibility in salary negotiation may threaten the financial viability of the league. It may be that the WNBA, which has historically struggled with generating profits as well as finding quality young talent,[14] simply does not have the financial security and large enough pool of high quality talent to justify a pay structure where every rookie contract is freely negotiated and fully guaranteed. To this end, a comparison between the NBA and WNBA in terms of their respective CBA must also account for their organizational constraints such as league profitability and potential pool of playing talent.

Lastly, this paper underscores an important distinction between efficiency and equity. The equity argument may be that player compensation in a sports league is not strictly about the amount of revenue the league is earning. What matters is the choices made by the leagues, the bargaining power of the workers, and the choices this power allows teams to make. The economic approach, however, is to examine the issue from an efficiency standpoint— I argue that neither is complete without the other. This paper shows that political arguments about the issue of equitable compensation in the WNBA must be made in conjunction with an economic one to foster more productive discussions.

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