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Is Offense Worth More than Defense in the National Basketball Association?

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Abstract

Motivated by the popular sports saying, “Offense sells tickets, defense wins championships,” we use Forbes revenue data to quantify whether offense really does sell more ‘tickets’ than defense in the National Basketball Association (NBA). Employing team offensive and defensive win shares as measures of offensive and defensive proficiency, we find offensively oriented teams generate the *same* amount of revenue as do defensively oriented teams, other things equal. Our results suggest that both profit-maximizing *and* win-maximizing teams should value offensively and defensively players equivalently (per unit). Thus, in an efficient free agent market, we would expect equilibrium player salaries for offensive and defensive production to be statistically equal (per unit). Coupled with recent findings that NBA teams pay players significantly more for offensive production than for defensive production (Ehrlich, Sanders and Boudreaux 2019), our current results indicate the existence of disequilibrium in the NBA free agent market. In an additional test of fan preferences, we transform existing Forbes revenue data into pre-revenue sharing revenue estimates based on the NBA’s current pool plan. Econometric results based on pre-revenue sharing revenue data provide further evidence that fans do not prefer offense to defense.

Keywords: Productivity, Revenue, Basketball, Offense, Defense

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1. Introduction

There is an ongoing discussion whether teams maximize profits or wins. A number of theoretical researchers assume the possible existence of both types [Dietl et al. 2009; Kesenne 2004; Kesenne and Pauwels 2006; Zimbalist 2003]. Leeds et al. (2018, 57-58) cite the NBA's Dallas Mavericks owner Mark Cuban as a prime example of a 'win-maximizer,' while labeling the Toronto Raptors ownership group as probable 'profit-maximizers.' More realistically, each team likely lies along a spectrum ranging from pure profit-maximization to pure win-maximization.

Since a point scored on offense carries approximately the same value (in terms of wins) as a point denied on defense, Ehrlich et al. (2019) correctly contend that win-maximizing NBA teams should value offense and defense equally (on average) on the free agent market. However, they find NBA teams pay players roughly 150% more for offensive production (per unit) compared to defensive production (per unit).[1] Given the NBA's salary cap, they posit a win-maximizing team could engage in arbitrage by choosing relatively underpaid defensive-oriented free agents. In other words, by choosing defensive-oriented players, a team could increase their wins per dollar spent.

In view of the Ehrlich et al (2019) findings, our current study recognizes that if teams are primarily profit-maximizing, the observed salary premium might exist because offense is *worth* more in terms of revenue generation; given the popular sports saying, "Offense sells tickets,

[1] In a study of Major League Baseball (MLB) position players, Ehrlich et al (2020) find that MLB free agents are also paid a premium for offensive production.

defense wins championships," we quantify whether offense really does sell more 'tickets' than defense in the NBA.[2] Since basketball highlights on television "almost exclusively show replays of thunderous dunks, flashy feeds and deep triples [Fromal, 2015]," then we contend it is certainly plausible that fans prefer offense to defense. That is, the revenue generated from an additional unit of offensive production might exceed the revenue generated from an additional unit of defensive production. In this scenario, profit-maximizing teams would be correct to pay more for offensive production, and only win-maximizers would be able to engage in arbitrage [as outlined by Ehrlich et al. (2019)].

Using team offensive and defensive win shares, we estimate the marginal revenue products (i.e. values) of offensive and defensive wins. We then test whether the marginal revenue product of an offensive win exceeds the marginal revenue product of a defensive win. By testing whether offense is truly worth more than defense, our study seeks to determine whether profit-maximizing teams are justified in paying a premium for offense. Importantly, if a defensive win were to carry the *same* worth (in terms of revenue generation) as an offensive win, then a salary premium paid for offensively oriented players would reveal that 1) arbitrage opportunities would exist for a team if they were win-maximizing *or* profit-maximizing, and 2) there would be disequilibrium in the NBA labor market.

[2] In a couple of papers examining on field performance, Gambarelli et al (2019) investigate the decision of soccer coaches in choosing an 'offensive' or 'defensive' strategy in soccer, while Robst et al (2011) find that defense is not more than offense in explaining winning in the National Football League. Ehrlich and Potter (2020) demonstrate that MLB fans do not have a preference for offense.

In an additional test of fan preferences, we transform (existing) post-revenue sharing revenue data to *pre*-revenue sharing revenue data for each team. Using these pre-revenue sharing revenue estimates, we also calculate the marginal revenue products (i.e. values) of offensive and defensive wins *prior* to revenue sharing, thereby obtaining a truer estimate of fan preferences, since the noise associated with revenue sharing is thereby reduced.

The remainder of the paper is structured as follows: Section 2 explains the use of team offensive and defensive win shares. Section 3 details the data, econometric modeling, and primary results. Section 4 explains how pre-revenue sharing revenue is calculated and estimates regressions with pre-revenue sharing revenue as the dependent variable. Section 5 concludes.

2. Team Win Shares

We model team offensive and defensive production in terms of win shares; these measures are quite attractive for three major reasons. First, they are highly predictive of actual winning (as we demonstrate later in this section). Second, they are *very* highly correlated with the team performance metrics known as offensive and defensive ratings (we demonstrate these correlations later in this section as well). Third, team offensive and defensive win shares are quite intuitive since they measure team ability in terms of team wins; hence, the value of offensive (defensive) wins can be directly compared to the value of actual team wins (as we demonstrate in section 3).

Offensive win shares and defensive win shares are calculated independently. These metrics were developed by the founder of Basketball Reference, Jason Kubatko [Casciaro, 2014], and are based on the work of Dean Oliver (2004). A number of sports economics researchers have also used player win shares in their analyses [e.g. Hoffer and Freide, 2014; Burdekin and Van, 2018;

Evans, 2018; Humphreys and Johnson, 2020]. A player's season offensive (defensive) win share total provides an estimate of how many wins that player contributed to their team on offense (defense). For example, the 2017-18 MVP, James Harden, had 11.6 offensive win shares and 3.8 defensive win shares. In other words, he produced 15.4 wins for his team (11.6 offensive wins and 3.8 defensive wins).

Team offensive and defensive win shares are also attractive for a number of practical considerations. First, both measures are calculated for each NBA player and published on basketballreference.com. Second, these data are freely available to academic researchers. Third, even if a player changed teams mid-season, their win share totals for each team are specified; hence, by summing all player win shares from each team we can calculate team win shares for both offense and defense.[3] Finally, once offensive and defensive marginal revenue product estimates are obtained, it is straightforward to estimate the entire marginal revenue product for a given player with the following stylized marginal revenue product equation:

1) $Marginal\ Revenue\ Product = OWS \cdot MRP^{OWS} + DWS \cdot MRP^{DWS}$

Where OWS (DWS) is the offensive (defensive) win shares contributed by a given player and MRP^{OWS} (MRP^{DWS}) is the marginal revenue product of an offensive (defensive) win. We obtain estimates for MRP^{OWS} and MRP^{DWS} in the next section. Although our approach follows the seminal work of Scully (1974), it is more precise since we are using an established measure of win shares instead of a crude estimate. In this way, win shares allow researchers to more easily estimate player marginal revenue product. For a competitive market, the standard economic

[3] This summation approach is not available for statistics like ESPN's adjusted real plus minus, as it is unclear how much a player contributed to each team (if a player changed teams mid-year).

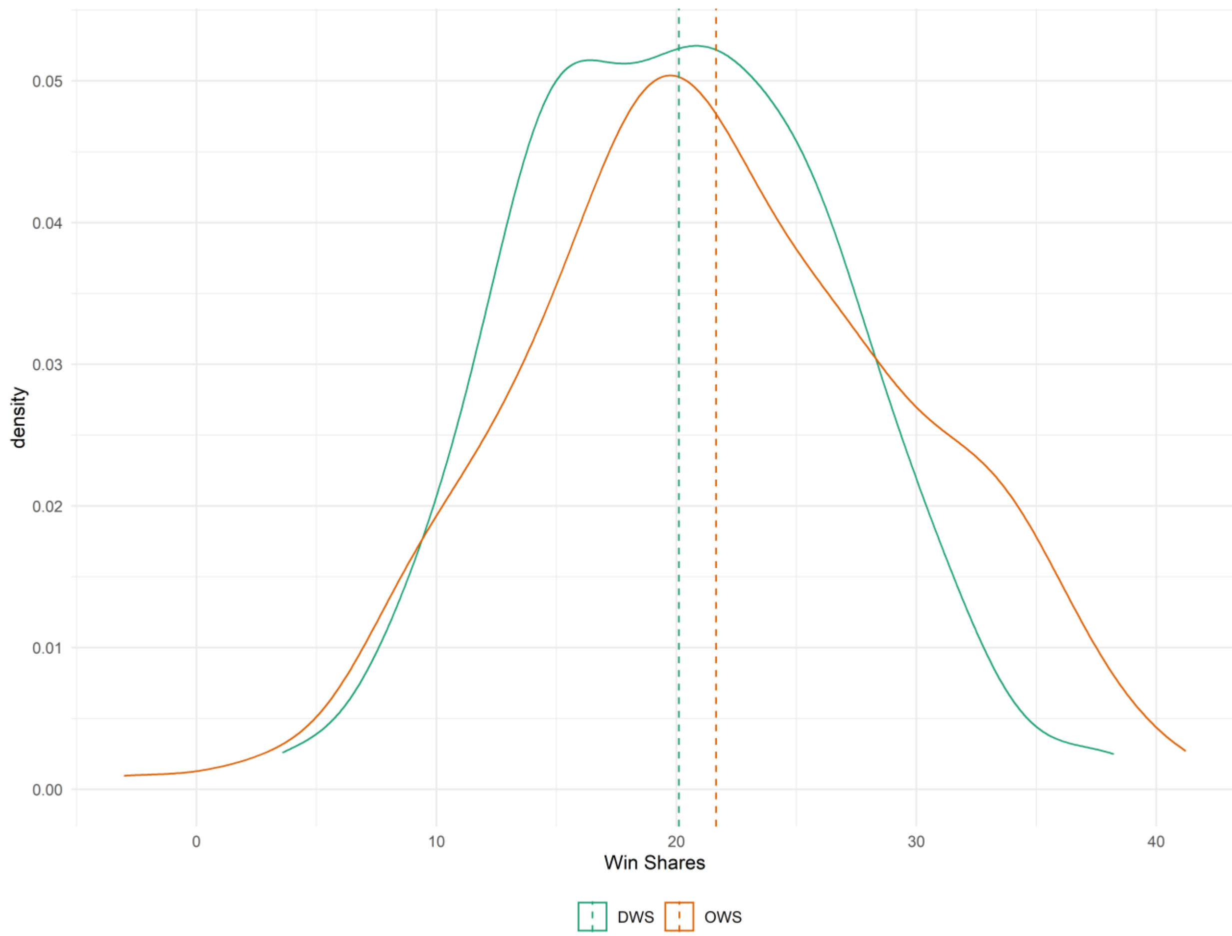
model reveals that players are paid equal to their marginal revenue product [see Leeds et al (2018, 263) for a discussion]. Summary statistics for win shares are presented in table 1.

Table 1: Summary Statistics: Offensive Win Shares (OWS) and Defensive Win Shares (DWS)

	Obs	Mean	St. Dev	25th	Median	75th
OWS	180	21.657	7.996	16.45	21.15	27.25
DWS	180	20.103	6.516	15.1	20.05	25

To further illustrate these distributions, the kernel density plots of team offensive and defensive win shares are presented in figure 1. Although distributions appear similar, offensive win shares are more dispersed than defensive win shares.

Figure 1: Kernel Density Plot: Offensive Win Shares (OWS) and Defensive Win Shares (DWS)



In order to check the robustness of offensive and defensive win shares in determining team wins, we specify the following OLS model and accompanying hypothesis:

$$2)\quad Wins_{i,t} = \beta_0 + \beta_1 OWS_{i,t} + \beta_2 DWS_{i,t} + \varepsilon_{i,t}$$

Hypothesis 1: $\beta_1 = \beta_2 = 1$. In this case, both offensive and defensive wins would have the same statistical relationship with actual team wins. Furthermore, an additional offensive (defensive) win would correlate one-to-one with an additional actual team win.

Table 2: OLS Regression Results with Wins as the Dependent Variable

	(1)
VARIABLES	Model 1
$OWS_{i,t}$	1.038***
	(0.0294)
$DWS_{i,t}$	1.025***
	(0.0361)
Constant	-2.070**
	(0.840)
Observations	180
R-squared	0.943

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results from table 2 provide evidence that team offensive and defensive win shares are good predictors of actual team wins. A Wald test indicates there is insufficient evidence to reject hypothesis 1 that $\beta_1 = \beta_2 = 1$. The p-value of this Wald test was 0.24. These results suggest there is a one-to-one relationship with team win share metrics (OWS and DWS) and actual wins.

In a separate robustness test, we measure the correlation between team defensive (offensive) win shares and team defensive (offensive) ratings. Team Defensive ratings (taken from basketballreference.com) measure the number of points allowed by a team per 100 possessions while team offensive ratings measure the number of points scored by a team per 100 possessions. Since offenses have tended to score more efficiently throughout the years of our sample [2013-14 to 2018-19], we corrected for this scoring ‘inflation’ by adjusting both team offensive and defensive ratings using the 2013-2014 season as the base year. The Pearson correlation coefficient between team defensive win shares and the ‘inflation’ adjusted team defensive ratings is -0.9995 and is statistically significant at the 0.000001 level (see figure 2 for a visual representation). Meanwhile, the Pearson correlation coefficient between offensive win shares and adjusted team offensive ratings is 0.9964 and is also statistically significant at the 0.000001 level (see figure 3 for a visual representation).

Figure 2: Team Defensive Win Shares and Adjusted Team Defensive Ratings

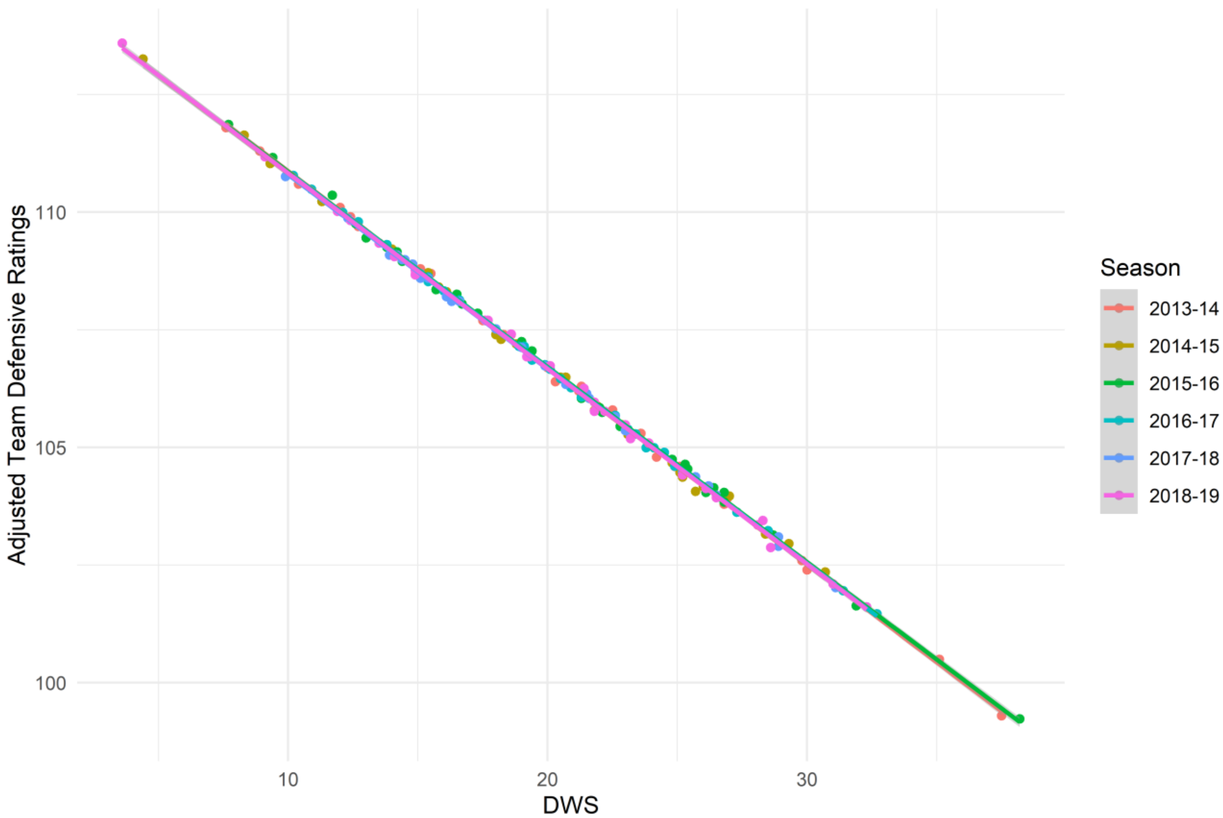
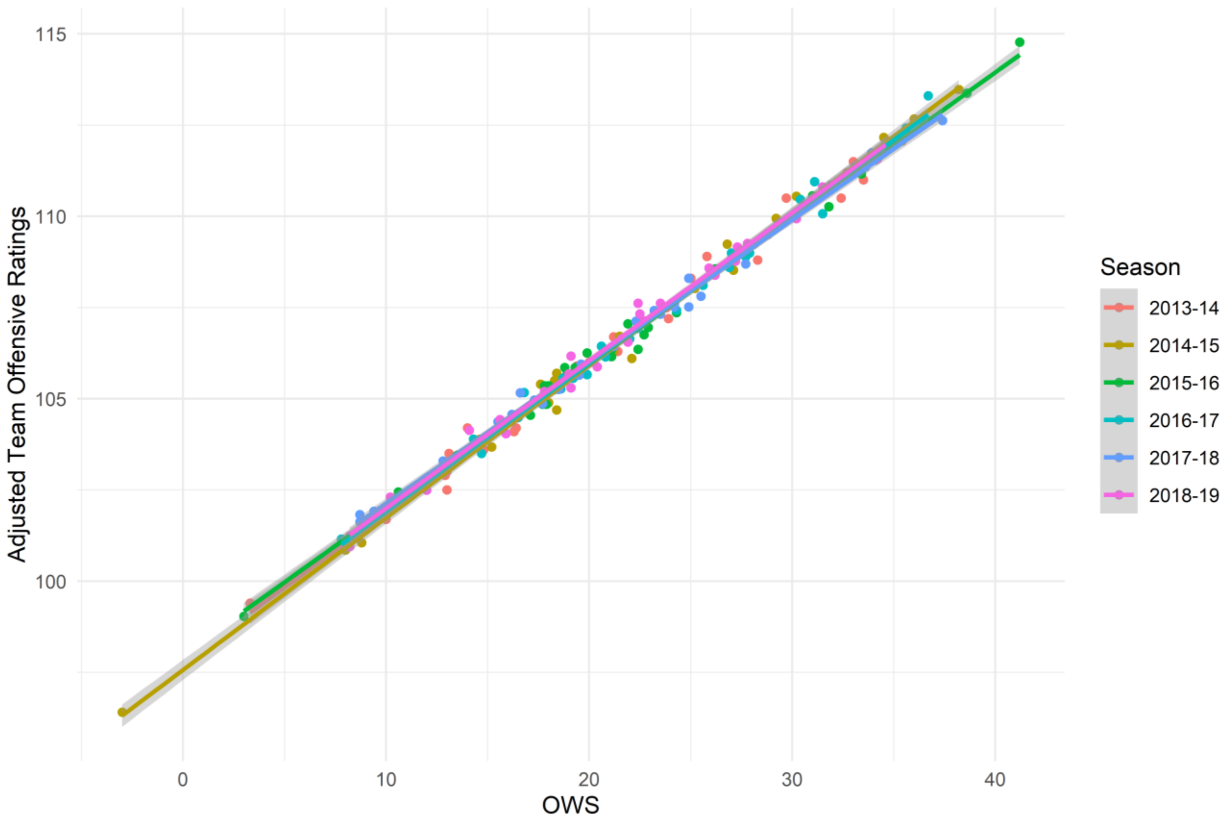


Figure 3: Team Offensive Win Shares and Adjusted Team Offensive Ratings



These results demonstrate that adjusted team defensive (offensive) ratings are essentially a perfect substitute for team defensive (offensive) win shares in terms of quantifying team defensive (offensive) quality. We select win shares as our productivity metric throughout the remainder of the paper since team 'wins' via defense (offense) is the more intuitive metric compared to points allowed (scored).

3. Econometric Modeling and Data

Our primary econometric specification is as follows:

$$3)\quad R_{i,t} = \beta_0 + \beta_1 OWS_{i,t} + \beta_2 DWS_{i,t} + \gamma X_{i,t} + \tau Year_i + \delta team_i + \varepsilon_{i,t}$$

Where $\beta_1 = MRP^{OWS}$ and $\beta_2 = MRP^{DWS}$. $X_{i,t}$ is a vector of controls [MSA income, MSA population, new stadium indicator] and $Year_i$ is a time trend. Table 5 presents the full summary statistics.

Table 5: Summary Statistics

	Obs	Mean	St.Dev	25^{th}	Median	75^{th}
Revenue	180	230.683	71.686	166.891	223.205	268.847
GDP per capita	180	63.135	13.382	53.886	62.111	69.196
Population	180	5606972	4935479	2306396	4408933	6265219
New Stadium	180	.056	.23	0	0	0
DeltaWL	180	0	.13	-.079	.012	.098
OWS	180	21.657	7.996	16.45	21.15	27.25
DWS	180	20.103	6.516	15.1	20.05	25

We use yearly [2013-14 to 2018-19] team revenue data collected from Forbes and adjust for inflation using data collected from the Bureau of Labor Statistics. We chose the sample years to avoid complications arising from the 2011-2012 lockout and the COVID-19 shortened 2019-20.[4] Forbes data include all team revenue generated from basketball operations (ticket sales, merchandise, concessions, television contracts, etc.) and accounts for revenue *after* sharing has taken place. We obtained real gross domestic product (by metropolitan statistical area) from the Bureau of Labor Statistics (2014-2018); it is reported in thousands of dollars. We obtained MSA Population data through the U.S. Census Bureau. We added Canadian equivalents for Toronto from StatCan, while obtaining new stadium data from the Wikipedia entry on current NBA stadiums [‘List of National Basketball Association Arenas,’ n.d.]. New stadium is an indicator equal to 1 when a team’s stadium was built 3 (or fewer) years prior to the relevant season. Delta

[4] We prefer to fully avoid data from 2011-12 (the lockout shortened season), and since we include a control variable calculated based on year *t*-1 observations, we therefore exclude the 2012-13 season from our sample.

win loss was obtained from basketballreference.com and is defined as a team's winning percentage in year *t* minus their winning percentage in year *t*-1. Win share measures (OWS and DWS) are discussed in section 2 above. Based on equation 3, we now formally state the relevant hypotheses:

Hypothesis 2 (null hypothesis): $MRP^{OWS} = MRP^{DWS}$. In this case, a profit-maximizing team would value offensively oriented free agents the same (per unit of production) compared to defensively oriented free agents. In a NBA labor market where there is an offensive salary premium, any team (profit-maximizing *or* win-maximizing) would have an opportunity to engage in arbitrage by choosing relatively underpaid defensive free agents (and disequilibrium would exist in the labor market).

Hypothesis 3: $MRP^{OWS} > MRP^{DWS}$. In this case, a profit-maximizing team would value offensively oriented players more (per unit of production) than defensively oriented free agents. In an NBA labor market where there is an offensive salary premium, only win-maximizing teams would have an opportunity to engage in arbitrage (and equilibrium could be present in the NBA labor market).

3.1 Model Selection

In choosing the econometric model, we first employed a Breusch and Pagan (1980) test to confirm that a panel model would be preferable to a pooled OLS model. The results overwhelming rejected the pooled OLS approach. We then implemented the 'xtoverid' command in Stata to test whether the coefficients produced by fixed effects and random effects were the same [Nichols, 2007]. The Sargan-Hansen test statistics from each of our primary specifications indicated that a fixed effects approach was preferable.[5] An article from Knowledge Base, "In stata, how do I test overidentification using xtoverid?", discusses how the 'xtoverid' command executes the "same approach described by Arellano (1993) and Wooldridge (2002, pp. 290-91)." A Wooldridge (2002) test—using the 'xtserial' command in Stata--rejected the null hypothesis of no first-order serial correlation. To correct for the first order autocorrelation, we use the fixed effects estimator derived by Baltagi and Wu (1999). Bradbury (2019) also selected the Baltagi and Wu (1999) fixed effects approach as superior for the same (above) general reasons.

3.2 Results

Using the approach developed by Baltagi and Wu (1999), we estimate several specifications and present our results in table 6. Note this approach reduces the number of observations by 30.

Table 6: Regressions with Yearly Team Revenue as the Dependent Variable

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
$OWS_{i,t}$	0.572*	0.923**	1.055***	0.990***
	(0.306)	(0.421)	(0.323)	(0.245)
$DWS_{i,t}$	0.453	1.037**	0.887**	0.883***
	(0.332)	(0.448)	(0.348)	(0.261)
$DeltaWL_{i,t}$		-19.17	-29.68**	-25.72***
		(16.79)	(13.42)	(9.791)
GDP per $capita_{i,t}$		6.341***	-1.267	-0.194
		(0.984)	(1.121)	(1.244)
$Population_{i,t}$		6.95e-05***	2.27e-05	2.12e-05
		(2.23e-05)	(1.71e-05)	(1.43e-05)

[5] The Hausman (1978) test was not possible since the 'rank of the differenced variance matrix did not equal the number of coefficients being tested' in each of our primary specifications.

New Stadium$_{i,t}$		8.435	12.36	3.594
		(11.27)	(8.703)	(6.674)
y2015				-35.76***
				(3.952)
y2016				-43.13***
				(4.979)
y2017				-14.20**
				(5.501)
y2018				-11.35***
				(4.087)
Time Trend			31.59***	
			(3.259)	
Constant	332.5***	-584.4***	-63,559***	164.1***
	(2.351)	(63.16)	(3,901)	(48.44)
Observations	150	150	150	150
Number of Teams	30	30	30	30

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Of the 4 specifications, Model 3 has the highest (overall) R-squared of 0.49 compared with (overall) R-squared measures of 0.09, 0.36, and 0.39 from models 1, 2, and 4 (respectively). The primary variables of interest, $OWS_{i,t}$ and $DWS_{i,t}$, generally have coefficients close to 1. Considering Model 3, the estimated marginal revenue product of an offensive win (MRP^{OWS}) is \$1.055 million whereas the estimated marginal revenue product of a defensive win (MRP^{DWS}) is \$887,000. A Paternoster test of coefficient equality does not reject hypothesis 2 that $MRP^{OWS} = MRP^{DWS}$; a one-sided test produces an associated p-value of 0.36 [see Paternoster et al (1998) for more information on this test]. Thus, an additional offensive win does not appear to generate more revenue compared to that of a defensive win. Consequently, in an NBA labor market where offensively oriented free agents receive higher salaries than defensively oriented free agents, a profit-maximizing team would be able to engage in arbitrage by allocating more resources to relatively underpaid defensive free agents (disequilibrium would exist in such a labor market). In other words, a team (win-maximizing *or* profit-maximizing) focusing on signing defensively-oriented players could generate more wins while spending the same total amount on salaries.

Control variable coefficients generally have the expected sign. GDP per capita$_{i,t}$ and Population$_{i,t}$ are both positive and statistically significant in Model 2, although they lose statistical significance in Models 3 and 4 (once time variables are included).

DeltaWL$_{i,t}$ (team winning percentage in year *t* minus winning percentage in year *t*-1) is negative and statistically significant in Models 3 and 4, suggesting a persistence effect moving from year *t*-1 to year *t*. In other words, if a team had a good year in year *t* after performing well in year *t*-1, revenue is estimated to be more in year *t* than if they had performed poorly in year *t*-1, *ceteris paribus*. New Stadium$_{i,t}$ is positive albeit statistically insignificant. However, since the proportion of teams in a new stadium (built within the past 3 years) is quite small, this result is not particularly surprising.

3.3 Accounting for Level of Team Offensive Orientation

As a robustness check, we introduce a new econometric specification as follows:

$$4)\quad R_{i,t} = \alpha_0 + \alpha_1 Wins_{i,t} + \alpha_2 Proportion_{i,t} + \gamma X_{i,t} + \tau Year_i + \varepsilon_{i,t}$$

Where $\alpha_1 = MRP^{win}$, $Wins_{i,t}$ refers to the actual number of wins for team *i* in year *t* and $Proportion_{i,t}$ is defined as $\frac{OWS_{i,t}}{WS_{i,t}}$, where $WS_{i,t}$ is defined as the total number of win shares generated by team *i* in year *t*. As $Proportion_{i,t}$ increases, a team becomes more offensively oriented. With the above econometric equation, we can test whether more offensively oriented teams generate more team revenue, *ceteris paribus*. Even among mediocre teams, $Proportion_{i,t}$ can vary widely. To illustrate, the 2014-15 Milwaukee Bucks won 41 (half) of their regular season games and had a $Proportion_{i,t}$ of 0.34, indicating only about one-third of their wins were generated by offense. Comparatively, the 2015-16 Houston Rockets *also* won 41 (half) of their regular season games but had a $Proportion_{i,t}$ of 0.63, a figure nearly *double* that of the Bucks. Interestingly, offensive juggernaut Houston was 15th in attendance while the defensive focused Milwaukee was 29th in attendance; similarly, Houston's revenue ($258 million) nearly doubled that of Milwaukee's.[6] Hence, our econometric specification tests whether *level* of offensive orientation matters in terms of revenue.

The R-squared measures (overall) for the fully specified models were 0.41 for model 3 and 0.43 for model 4. The estimates from table 7 reveal a statistically insignificant relationship between $Proportion_{i,t}$ and team revenue, *ceteris paribus*. In each specification, the standard errors of the $Proportion_{i,t}$ are at least double that of the coefficients, with p-values of at least 0.67. These results strongly suggest a statistically insignificant relationship between $Proportion_{i,t}$ and team revenue. We can also specify the following hypothesis:

Hypothesis 4: $MRP^{Win} = MRP^{OWS}$ and $MRP^{Win} = MRP^{DWS}$; in this case, actual wins would have the same impact on team revenue as do offensive and defensive wins.

Table 7: Regressions with Yearly Team Revenue as the Dependent Variable

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
$Wins_{i,t}$	0.517**	1.085***	0.968***	0.998***
	(0.200)	(0.331)	(0.243)	(0.193)
$Proportion_{i,t}$	7.811	-2.102	6.497	4.468
	(18.07)	(20.20)	(16.17)	(11.64)
$DeltaWL_{i,t}$		-26.92	-32.45**	-31.03***

[6] We note a large factor in this comparison is that Houston is a large market while Milwaukee is a small market.

		(17.30)	(13.68)	(10.01)
GDP per capita$_{i,t}$		6.325***	-1.151	-0.0148
		(0.983)	(1.115)	(1.228)
Population$_{i,t}$		7.26e-05***	2.55e-05	2.52e-05*
		(2.23e-05)	(1.71e-05)	(1.42e-05)
New Stadium$_{i,t}$		8.642	12.35	3.568
		(11.17)	(8.675)	(6.566)
y2015				-34.66***
				(3.831)
y2016				-41.75***
				(4.840)
y2017				-12.97**
				(5.364)
y2018				-10.66***
				(3.993)
Time Trend			31.16***	
			(3.237)	
Constant	328.8***	-603.3***	-62,719***	125.5***
	(2.805)	(62.50)	(3,873)	(46.99)
Observations	150	150	150	150
Number of Teams	30	30	30	30

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Estimates reveal that a win generates an additional $0.968 million dollars ($MRP^{win}$) is very close to the estimates of MRP^{OWS} and MRP^{DWS} from table 6 where MRP^{OWS} =$1.055 million and MRP^{DWS} =$0.887 million. In tests of coefficient equality [Paternoster, 1998], hypothesis 4 (MRP^{Win}= MRP^{OWS} and $MRP^{Win} = MRP^{DWS}$) could not be rejected, suggesting the marginal revenue product of an offensive (defensive) win is equivalent to the marginal revenue product of an *actual* win. This provides evidence that offensive and defensive win shares have the same statistical relationship with team revenue as does *actual* team wins.

Signs and statistical significance of the control variables in table 7 were quite similar to those from table 6. In order to account for potential non-linearities between team performance and revenue, we included squared terms for offensive and defensive win shares (equation 4) as well as a squared term for actual wins (equation 5). These squared terms were not statistically significant and results are available from the authors upon request.

3.4- Implications and Case Study

In the introduction, we discuss how NBA teams are win-maximizers or profit-maximizers. Most likely, the league has a mix of win *and* profit maximizers. Our above econometric results suggest offensive and defensive wins are equally valuable as revenue generators in the NBA, demonstrating that profit-maximizing teams should value offense at the same rate as defense on the free agent market. Our conclusion matches Ehrlich et al.'s (2019); i.e. that *win-maximizers* should value offense and defense equally.

A case study from the recent free agent market can help articulate these insights. During the 2019 free agent market, Derrick Rose and T.J. McConnell both signed 2-year contracts with the Pistons and Pacers, respectively. Both players were point guards coming off seasons with similar win share totals (3.0 for Rose and 2.9 for McConnell). Even though McConnell was 4 years younger and had a much better health history, Rose signed for $15 million while McConnell received only $7 million. Since Rose was worth 2.6 offensive win shares the previous year while McConnell was worth only 1.2 offensive win shares, this illustrates an offensive premium paid for offensive production as described by Ehrlich et al. (2019). Ehrlich et al. (2019) would have advised a win-maximizing team to sign the relatively undervalued player (like McConnell) since doing so would increase the expected number of wins (by freeing up cap space to sign another win producing player). We would also advise a *profit-maximizing* team to focus on a player like McConnell, since defensive production could be purchased more cheaply (per win) while the marginal revenue product of a defensive win is equivalent to that of an offensive win. Therefore, the conclusion teams should pay for defense at the same rate as offense (per unit) applies to both *win-maximizing* and *profit-maximizing* teams.[7][8]

Thus far, we have shown that profit-maximizing teams should value offensive and defensive production equally. However, the NBA has a system of revenue sharing that distorts the revenue generation process since high revenue teams transfer revenue to low revenue teams. In order to more fully test whether "offense sells tickets," we take revenue sharing into account in the next section.

4. Revenue Prior to Revenue Sharing

Since the NBA has a system of revenue sharing, the previous estimations *distort* the true preferences of fans. For example, the fan spending generated by an additional win by the Lakers is not entirely *retained* by the Lakers. Instead, the league's revenue sharing policy dictates that large market teams like the Lakers distribute some of their fan's spending to small revenue teams. In order to obtain marginal revenue product estimates reflecting *true* fan spending (i.e. preferences), then the correct revenue measure would be revenue *prior* to sharing. Thus, we model pre-sharing revenue by assuming the NBA operates a straight 50% pool plan. This approach is similar to the Major League Baseball pre-revenue sharing models of Rockerbie and Easton (2018) and Ehrlich and Potter (2020). First, we note that for the league:

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[7] Through the first half of their contracts (from a season shortened by COVID-19), McConnell (3.4 WS, 1.7 OWS, 1.7 DWS) has outperformed Rose (2.5 WS, 1.8 OWS, 0.7 DWS). However, McConnell's salary is less than half that of Rose's. Rose has still been offensive oriented and McConnell has still been defensive oriented.

[8] Using Forbes revenue data, Berri et al (2015) also find that marginal revenue product estimates for NBA players are smaller than what they are *actually* paid in the free agent market. They use a bargaining model to explain this result. Since we are analyzing the *difference* between MRP^{OWS} and MRP^{DWS}, it is beyond the scope of our current study to explain the difference between estimated marginal revenue products and observed salaries.

$$\left(\sum_{i=1}^{30} R_i\right) = \left(\sum_{i=1}^{30} R_i^{Pre}\right) \qquad 6)$$

Where R_i^{Pre} is team *i*'s revenue (pre-sharing) in year *t* and R_i is team *i*'s revenue (post-sharing). In other words, equation 6 states total league revenue is equivalent pre- and post-sharing.

For team *i*:

$$0.5R_i^{Pre} + 0.5\left(\frac{1}{30}\right)\left(\sum_{i=1}^{30} R_i^{Pre}\right) = R_i \qquad 7)$$

Where 0.5 is the proportion of each team's revenue (pre-sharing) that goes to the league's pool where the total amount of the pool is then dispersed equally between each team.

Substituting:

$$0.5R_i^{Pre} + 0.5\left(\frac{1}{30}\right)\left(\sum_{i=1}^{30} R_i\right) = R_i \qquad 8)$$

This substitution is necessary in order to calculate pre-revenue sharing for team *i* with observable Forbes data.

Rearranging:

$$R_i^{Pre} = \frac{R_i - 0.5\left(\frac{1}{30}\right)\left(\sum_{i=1}^{30} R_i\right)}{0.5} \qquad 9)$$

Equation 9 allows us to estimate each team's revenue (pre-sharing) with the (post-sharing) revenue available from Forbes. This equation represents a situation wherein a league has a 50% straight pool plan. Such a plan has the largest revenue teams (those above the mean) paying in and the smallest teams (those below the mean) receiving from the pool.

Our assumption that revenue sharing is a 50% straight pool plan fits well with several features from the actual CBA agreement. According to Coon (1999-2020), “the concept behind the plan is that teams contribute an equal percentage of their total revenues into a common pool (adjusted for certain expenses such as arena expenses), then receive an allocation equal to a 1/30 share of the pool.” Each team’s total revenues are calculated through what the CBA defines as Basketball Related Income (BRI). Although BRI is likely highly correlated with the revenue figures produced by Forbes, the numbers are not the same. Furthermore, per team BRI figures are unavailable to researchers. Thus, we use the Forbes data to estimate team revenue prior to revenue sharing, since actual monetary transfer between teams is determined by the unobserved team BRI figures. There are also a number of exceptions in how funds are distributed via the pool [Coon, 1999-2020]. However, we unable to include these exceptions in our model of revenue (pre-sharing) due to data limitations.

In determining the amount of BRI paid to players, the two most recent CBAs (2011, 2017) have a stipulation that the player’s share of Basketball Related Income is a band from 49%-51% [Aldridge, 2016]. However, Coon (1999-2020) also writes that players are guaranteed 50% of the league’s projected BRI for the upcoming year, “plus (or minus) 60.5% of the amount by which revenues exceed (or fall short of) the forecasts, with a lower limit of 49% of BRI and an upper limit of 51% of BRI.” Since the percentage paid by each team to the league wide revenue sharing pool [Coon, 1999-2020] is determined by the amount paid to player salaries (between 49% and 51%), we use the midpoint (50%) as the amount contributed to the pool by each team for our estimation of yearly team pre-revenue sharing revenue. Table 8 presents summary statistics of both the Forbes revenue figures (post-revenue) and our own estimates of pre-revenue sharing revenue.

Table 8: Revenue Summary Statistics

	Obs	Mean	St. Dev	25th	Median	75th
Revenue	180	230.683	71.686	166.891	223.205	268.847
Pre-Sharing Revenue	180	230.683	119.389	144.509	199.549	281.323

Figure 4 illustrates the distributions of post-revenue sharing revenue and pre-revenue sharing revenue. By definition, the means (the dotted line) of each distribution are equivalent. However, the pre-revenue sharing revenue distribution shows more dispersion than the post-revenue sharing revenue distribution.

Figure 4: Kernel Density Plots Comparing Distributions Before and After Revenue Sharing

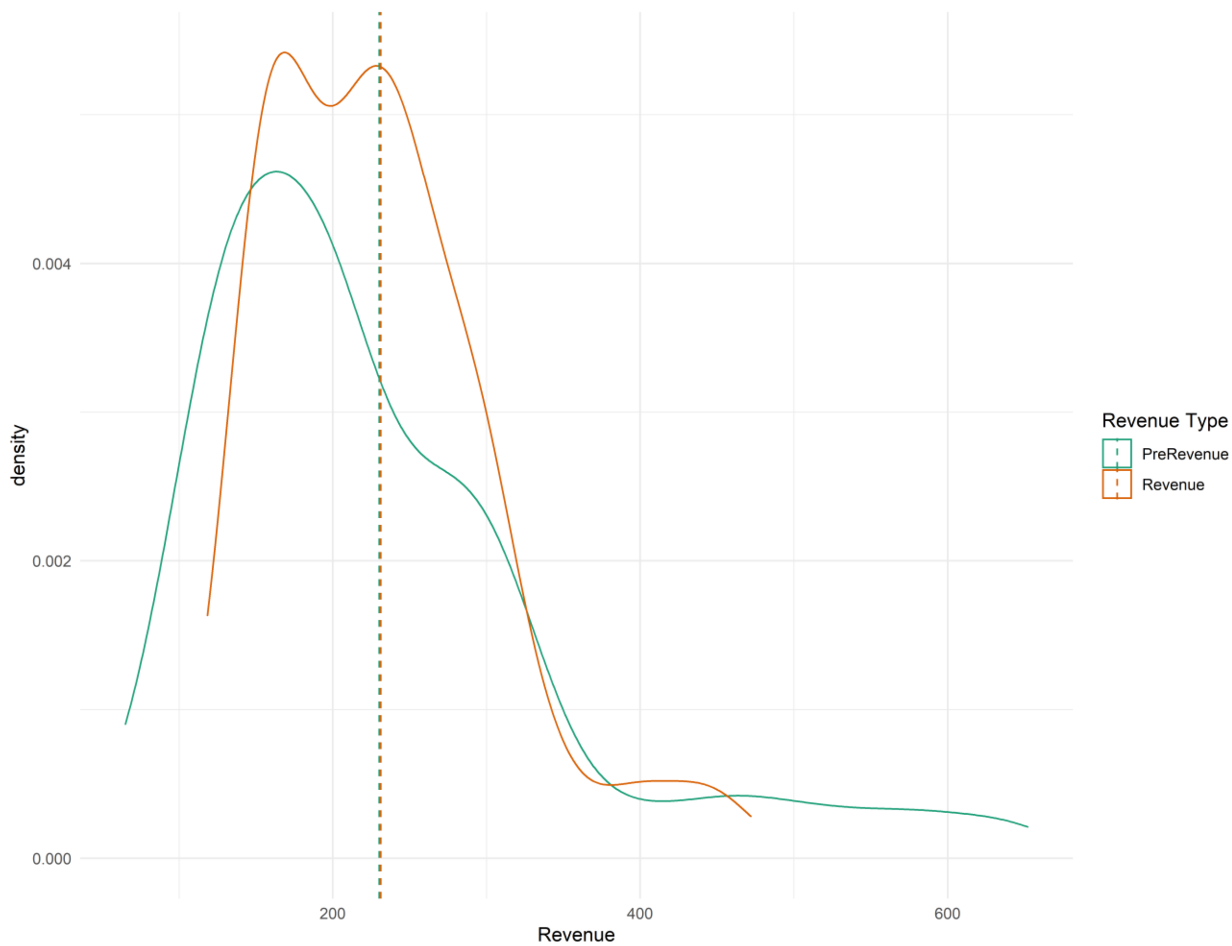
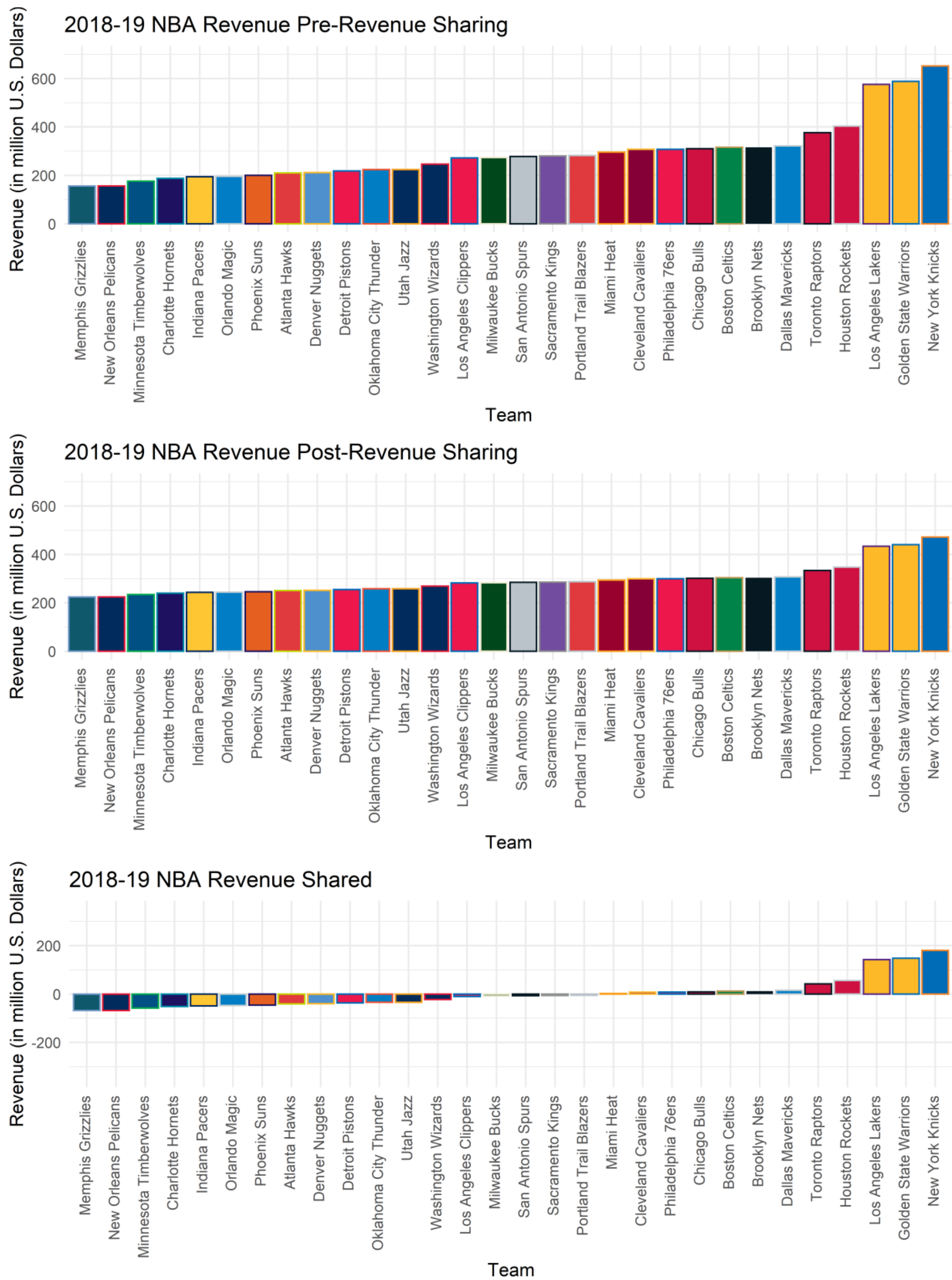


Figure 5 illustrates the team-by-team before-and-after process of revenue sharing from 2018-2019. The pre-revenue sharing histogram is noticeably more dispersed than the post-revenue sharing histogram.

Figure 5: Comparison of Team Revenue Before and After Revenue Sharing during the 2018-19 NBA Season



Our *a priori* assumption is that a win is more valuable pre-revenue sharing. Our econometric models:

$$10)\ R_{i,t}^{pre} = \beta_0 + \beta_1 OWS_{i,t} + \beta_2 DWS_{i,t} + \gamma X_{i,t} + \tau Year_i + \varepsilon_{i,t}$$

$$11)\ R_{i,t}^{pre} = \alpha_0 + \alpha_1 Wins_{i,t} + \alpha_2 Proportion_{i,t} + \gamma X_{i,t} + \tau Year_i + \varepsilon_{i,t}$$

These are the same econometric models specified in section 3, except pre-revenue sharing revenue ($R_{i,t}^{pre}$) is the dependent variable instead of post-revenue sharing revenue ($R_{i,t}$). In regards to equation 10, $\beta_1 = MRP_{pre}^{OWS}$ and $\beta_2 = MRP_{pre}^{DWS}$ and variables $OWS_{i,t}$ ($OWS_{i,t}$) represent team offensive (defensive) win shares. For equation 11, $\alpha_1 = MRP_{pre}^{Wins}$ and $Wins_{i,t}$ is the (actual) number of team wins in a given season. $Proportion_{i,t}$ is the fraction of team win shares deriving from offense. We now form the following hypotheses:

Hypothesis 5: $MRP_{pre}^{OWS} = MRP_{pre}^{DWS}$. In this case, fan preferences for offensive and defensive wins would be (statistically) equivalent.

Hypothesis 6: $MRP_{pre}^{OWS} > MRP_{pre}^{DWS}$. In this case, fans would have a preference for offensive wins compared to defensive wins (prior to revenue sharing).

Hypothesis 7: $MRP_{pre}^{OWS} = MRP_{pre}^{Wins}$ and $MRP_{pre}^{DWS} = MRP_{pre}^{Wins}$. In this case, actual team wins would have an equivalent impact on revenue as offensive (defensive) wins.

Hypothesis 8: $MRP^{OWS} < MRP_{pre}^{OWS}$ and $MRP^{DWS} < MRP_{pre}^{DWS}$; economic research has found that revenue sharing acts like a tax on the value of wins [see Leeds et al. (2018, 135) and Solow and Krautmann (2007)]; therefore, we expect *a priori* that post-revenue sharing coefficients would be larger than pre-revenue sharing coefficients.

Table 9: Regression Results with Pre-Revenue Sharing Revenue as the Dependent Variable.

VARIABLES	(1) Model 1	(2) Model 2
$OWS_{i,t}$	2.054***	
	(0.532)	
$DWS_{i,t}$	1.781***	
	(0.569)	
$Wins_{i,t}$		1.963***
		(0.409)
$Proportion_{i,t}$		11.74
		(25.97)
$DeltaWL_{i,t}$	-55.77**	-63.49***
	(21.61)	(22.07)
GDP per $capita_{i,t}$	-1.759	-1.543
	(2.081)	(2.070)
$Population_{i,t}$	4.10e-05	4.71e-05
	(2.92e-05)	(2.92e-05)
New $stadium_{i,t}$	16.79	16.93
	(14.30)	(14.18)
Time Trend	33.38***	32.56***
	(6.340)	(6.305)
Constant	-67,281***	-65,684***
	(6,211)	(6,127)
Observations	150	150
Number of Teams	30	30

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Both models have the same R-squared (0.46).[9] Using (estimated) pre-revenue sharing revenue in the above regressions provides a better estimate of true fan preferences (in terms of their spending) compared to models using post-revenue sharing revenue (tables 6 and 7). From the first specification, the estimated marginal revenue product of an offensive win (2.054) is slightly larger than that of a defensive win (1.781); a Paternoster test does *not* reject hypothesis 5 that MRP_{pre}^{OWS}=MRP_{pre}^{DWS} (with a p-value of 0.35 in a one-sided test). Hence, fans do not appear to have a clear preference for offense.

Considering hypothesis 7, Model 2 produces a MRP_{pre}^{Win} estimate that is *not* statistically different from MRP_{pre}^{OWS} and MRP_{pre}^{DWS}in Paternoster (1998) tests for coefficient equality [with p-values of at least 0.79 in each (two-sided) test]. This supports the notion that *actual* team wins have an equivalent impact (in a statistical sense) on pre-revenue sharing revenue as do offensive and defensive win shares. Furthermore, the coefficient for $Proportion_{i,t}$is *not* statistically significant (0.70 p-value) in model 2, demonstrating that level of offensive production, *ceteris paribus*, does not statistically influence pre-revenue sharing revenue.

Estimates for MRP_{pre}^{OWS} and MRP_{pre}^{DWS} from table 9 (regression 1) are roughly double that of post-revenue sharing estimates for MRP^{OWS} and MRP^{DWS} from table 6 (regression 3). Considering hypothesis 8, MRP_{pre}^{OWS} is statistically significant and larger than MRP^{OWS} (with a p-value of 0.05 in a one-sided Paternoster test). Similarly, MRP_{pre}^{DWS} is statistically significant and larger than MRP_{pre}^{DWS} (p-value of 0.09 in a one-sided test). Thus, wins are shown to be more

[9] We also estimated the same specifications as tables 6 and 7 from section 3, although we only report the specifications with the highest R-squareds in table 9. Full results are available from the authors upon request.

valuable in the absence of revenue sharing. In other words, revenue sharing acts like a 'tax' on winning.

One final observation is that the controls from table 9 have similar signs and statistical significance as do tables 6 and 7. A noticeable difference is that the $\text{DeltaWL}_{i,t}$ coefficients from the pre-revenue sharing regressions are about twice the size (in absolute value) as the post-revenue sharing regressions.

5. Conclusion

Using Forbes revenue data and team offensive and defensive win shares, we find no statistical difference between the marginal revenue product of an offensive win compared with that of a defensive win. We confirm these findings both before and after revenue sharing. Therefore, we conclude that fans do not prefer offense to defense in terms of their spending.

Implications for profit-maximizing team decision makers are clear: offensive production should be compensated at the *same* rate as defensive production. Our results are particularly interesting given that Ehrlich et al. (2019) demonstrate teams compensate offensive production roughly 150% more than defensive production in the NBA (in terms of salaries). Ehrlich et al. (2019) point out *win*-maximizing teams should also pay for offensive production at the same rate as defensive production. Thus, in an efficient market, we would expect the equilibrium price for offensive and defensive production to be equal (per unit). Coupled with the findings of Ehrlich et al (2019), our current results suggest disequilibrium in the NBA labor market. Future researchers should continue studying the NBA labor market in order to confirm (or disprove) the offensive premium discovered by Ehrlich et al. (2019).

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