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Predicting the WNBA Draft: What Matters Most from College Performance?

Jill Harris[1] and David J. Berri[2]

[1] Pomona College
[2] Southern Utah University

Jill S. Harris, PhD, is a visiting assistant professor of economics and teaches Economics of Sport and Economics of Crime. Her research interests include the nature and behavior of the National Collegiate Athletic Association (NCAA), women in sport, acquatic sports, and non-compliance behavior.
David J. Berri, PhD, is a professor of economics in the Department of Economics and Finance. His current research focuses on the economics of sports, specifically the topics of consumer demand, competitive balance, worker productivity, and women in sport.

Abstract
The reverse-order draft has been the subject of a number of studies in the economics literature. These studies generally examine the quality of decisions teams make in this process. The results in the studies of the NFL, NBA, and MLB all highlight problems with the player evaluation process. This study contributes to this literature and the broader literature on gender economics via an examination of the WNBA. Similar to other studies, we also find issues with decision-making in the WNBA draft.

Keywords: WNBA, draft, gender, basketball

Introduction
The Women's National Basketball Association (WNBA) utilizes a version of the reverse-order draft lottery similar to the NBA. While previous research has examined factors impacting the draft picks and subsequent professional performance in the NBA,[1] we do not believe this subject has been explored for the WNBA. In fact, little has been published on this league. This particular study will build upon the work of Berri and Krautmann (2013), which presented a model of player performance for the WNBA. This work will be paired with the approach to the NBA draft introduced by Berri, Brook, and Fenn (2011). In the end, this research will explore both what factors determine draft position in the WNBA and how such factors relate to subsequent performance.

Conceived in 1996, the WNBA has experienced the typical growing pains of many relatively young sports leagues.[2] As we saw in the early history of the NBA, teams in the WNBA have come and gone while profits and attendance have expanded and contracted. With respect to the number of teams, the league began with eight teams in

1997, expanded to 16 teams by 2000, before contracting to its current 12 teams by 2010. Currently the league remains with just the following teams: Atlanta Dream, Chicago Sky, Connecticut Sun, Indiana Fever, Los Angeles Sparks, Minnesota Lynx, New York Liberty, Phoenix Mercury, San Antonio Silver Stars, Seattle Storm, Tulsa Shock, and Washington Mystics.

Relative to the NBA, these teams appear—when we look at with-in season variation—to be somewhat competitive.[3] When we look at league championships, though, we see less competition. Of the 18 franchises that have existed in the WNBA, only eight have ever won a title. And 15 of the league's 17 titles have been won by just six organizations.

One proposed solution to such imbalance embraced by sports leagues throughout North America is the reverse-order draft. This institution rewards the worst teams in a league with a choice of the best available talent not currently employed in the league.[4] For this to improve competitive balance, the teams selecting first must be selecting more productive players than those taken later. There is a problem, though, with the selection process. At the time of the draft a team has not seen how a given player will perform against the talent seen in the professional league. Consequently, it is possible the worst teams do not actually get better via the draft.

This is essentially the story told by much of the previous research on drafts in professional sports. Both Massey and Thaler (2006) and Berri and Simmons (2011) uncovered problems with how talent is selected in the NFL draft. With respect to the NBA, Kahn and Sherer (1988) reported no statistical relationship between draft position and a player's statistical performance in college. More recently, Berri et al. (2011) report that draft position is related to scoring totals,[5] but other factors—like shooting efficiency and rebounds—that are more closely aligned with winning were not found to matter much in a player's draft position. These results are similar to those of Coates and Oguntimein (2010). Using data from 1987 to 1989, the authors found points scored were important for draft position, but not indicative of professional point scoring. Rebounds, blocks, and assists were correlated more with pro performance.

The importance of scoring in player evaluations in the NBA is not a new finding. Berri and Schmidt (2010) offer evidence of the primacy of scoring in terms of salary allocation.[6] But a study of salaries in the WNBA is problematic. The collective bargaining agreement in the WNBA results in salaries that are much more regimented and far lower than the NBA.[7] Consequently this study into player evaluation in the WNBA turns to the draft, an arena that allows us to examine which factors decision-makers consider in evaluating basketball talent.

Research on the WNBA in this area is interesting for at least four reasons. More broadly, an examination of decision-making in sports—where labor productivity data is abundant—allows one to assess whether or not decision-makers act in a fashion consistent with the neoclassical model. Related to this point, decision-makers in the NBA have been found to focus on scoring (seemingly) above all else when evaluating player talent. Prior research establishes that efficiency in scoring is not significant in player evaluation. Will the WNBA management suffer the same efficiency blindness?

A third reason for interest is the analysis of player productivity from the college draft into the pro league. Specifically, can we determine whether the factors highlighted on draft day predict WNBA performance? Berri et al. (2011) reviewed how Hollinger

(2003) and Oliver (2004) assert that wins are determined by a team's ability, relative to its opponent, to elicit points from its possessions. Gaining possession is a function of rebounding, steals, and turnovers. We are curious whether these factors have more impact in the WNBA than they did in the Berri et al. (2011) research.

Finally, this research may contribute to the broad literature on gender economics and how the work of females and males is evaluated. The WNBA and NBA are closely linked; the NBA initially owned the WNBA and many decision-makers in the former have extensive experience with the latter. Papers published in organizational behavior, higher education, and other behavioral journals point to differences in performance evaluation based on gender. For example, in a widely cited paper, Basow (1995) found significant interactions between teacher gender and student gender in student course evaluations. Male professors' evaluations were not impacted by student gender while female professors' evaluations were impacted by student gender. Female instructors received their lowest ratings from male students and highest ratings from female students. This type of effect is reported in a variety of studies across multiple fields.[8] Our findings suggest female player performance does not appear to be evaluated differently than male player performance. If this result holds then it would certainly be of interest to audiences outside of sports economics.

Modeling the Draft

This study of the draft uses amateurs chosen by WNBA teams from NCAA programs. International players are excluded since comparable statistics for their pre-professional experience are not available.[9] We collected draft data from 2010 to 2013 and college performance data from the drafted players' last year of college play. Summary statistics for our data are detailed in Table 1. The sample is small—only 128 players. However, the model generates results similar to those found in Berri et al. (2011), suggesting managers in the WNBA suffer similar impairments to the NBA when it comes to assessing player performance and productivity.

The average player in our sample is 6-foot tall, the tallest is 6-foot-6, and the smallest is 5-foot-4. Unlike the male athletes drafted into the NBA, all the female players in the sample completed four years of college, making the age range tighter. The average age is a little over 22 while the oldest players were 24 when drafted. Another interesting feature of the data is that more draft picks come from the SEC than any other conference (the ACC and PAC 10 have the honors in the NBA study conducted by Berri et al.). Almost twice the number of draft picks in the WNBA played in the NCAA Final Four versus the NBA. Since the dependent variable is draft position, a variable that positively impacts draft position will have an estimated coefficient with a negative sign.[10]

As with Berri et al. (2011), the dependent variable is draft pick selection number. This value ranges from 1 to 36 in each draft year (12 teams with a three-round draft). Each player's performance is adjusted for position played as in other prior work by Berri and Berri et al.[11]

What factors impact draft position? We begin with player performance in college. As noted by Berri et al. (and in contrast to the work of Kahn and Scherer [1988]) players with better college performance statistics should be drafted higher. After all—as noted earlier—the primary stated purpose of the draft is to give poor performing teams

Table 1. Descriptive Statistics for Dependent and Independent Variables (2010-2013)*

Variables	Label	Mean	SD	Min.	Max.
Draft position	**PICK**	18.37	10.33	1	36
Points scored	PTS	18.80	4.70	8.3	31.03
Rebounds	REB	6.18	3.43	0.35	13.17
Assists	AST	4.35	1.92	1.36	13.60
Steals	STL	2.80	0.93	1.18	5.42
Blocked Shots	BLK	0.86	1.14	-1.57	3.29
Personal Fouls	PF	2.45	0.76	0.81	4.94
Turnover %	TOPER	0	0	0	0
3 pt field goal %	3FGPER	0.29	0.14	0	0.75
2 pt field goal %	2FGPER	0.47	0.07	0.31	0.71
Free Throw %	FT	0.74	0.09	0.47	0.89
Age	AGE	22.39	0.55	22	24
Height, in	RELHT	72.10	2.20	64.80	78.20
Final Four player	DFIN4	0.16	0.37	0	1.0
Played in ACC	DACC	0.19	0.39	0	1.0
Played in PAC 12	DPAC12	0.10	0.31	0	1.0
Played in Big East	DBIGEAST	0.05	0.22	0	1.0
Played in SEC	DSEC	0.24	0.43	0	1.0
Played in Big Ten	DBIG10	0.09	0.29	0	1.0
Played in Big 12	DBIG12	0.09	0.29	0	1.0
Played in Conf USA	DCONFU	0.03	0.17	0	1.0
Played in Mt West	DWEST	0.09	0.29	0	1.0
Played in Colonial	DCOLON	0.01	0.10	0	1.0
Played in American	DAMER	0.08	0.27	0	1.0
Played in Sun	DSUN	0.01	0.10	0	1.0
Played Center	DC	0.14	0.34	0	1.0
Played Forward	DF	0.40	0.49	0	1.0
Played Guard	DG	0.45	0.50	0	1.0

* There are 128 observations. Notes: PTS, REB, AST, STL, BLK, and PF are per 40 min and adjusted for position played. TOPER is also adjusted for position played. Turnover Percentage = [(Turnovers)/(Turnovers + Field Goal Attempts + 0.44*Free Throw Attempts)] Sources: college performance data from NCAA.com; height data is from WNBA.com.

access to better players. Next, height and age are included in the model. Although it is cliché: you cannot teach height. Particularly in the female game we might expect the short supply of tall women to be even more critical to the draft decision. Because the advantage of height relative to position played could also impact draft position we model height relative to position.[12]

Given the attention paid to age and experience in the NBA it makes sense to include age as a control characteristic in our sample. However, the women's game is not as lucrative at the professional level. Female athletes have fewer incentives to leave college early to enter the WNBA. Therefore, we do not expect age to be as important in the draft selection story here.

In addition to the regressors mentioned above we include dummy variables for athletic conference to capture the difference in quality of college team played for and the degree of competition faced. We also include a dummy for Final Four experience. As with the NBA, experience in post-season play may be perceived as a plus by decision-makers and should improve draft position. Finally, dummy variables for the draft class years are included in the model for potential variations in the draft pool year to year over the sample.

To summarize, we expect draft pick to be influenced by college performance (captured by PROD—a vector of player specific position adjusted performance statistics including points, rebounds, steals, blocked shots, assists, turnovers, and measures of shooting efficiency), RELHT or relative height, AGE, college conference given by dummies for each, experience in post-season play (DFIN4), and relative quality of pool of draftable athletes in a given year (captured by a time dummy for each year, D10, etc.). These influences are all noted in Equation 1, which we will estimate in an effort to explain where a player will be chosen in the WNBA draft.

$$PICK_n = \beta_0 + \alpha_N PROD + \beta_1 RELHT + \beta_2 DFIN4 + \beta_3 DCHAMP + \beta_4 AGE + \beta_5 DACC + \beta_6 DPAC12 + \beta_7 DBIGEAST + \beta_8 DSEC + \beta_9 DBIG10 + \beta_{10} DBIG12 + \beta_{11} DAMER + \beta_{12} DCOLON + \beta_{13} DWEST + \beta_{14} DCONFU + \beta_{15} DSUN + \beta_{16} DC + \beta_{17} DF + \beta_{18} DG + \alpha_J DYEAR + e_{it} \quad (1)$$

Empirical Findings

Equation 1 is estimated with four years of draft data. Estimation of the model was conducted with both a Poisson Distribution model and a Negative Binomial model.[13] The estimations are reported in Table 2. Since the Poisson and Negative Binomial models return coefficients from a Maximum Likelihood estimation process the coefficients are not equivalent to estimated slopes. The coefficients are used to estimate marginal effects at the sample means. These marginal effects are reported in Table 2.

Before discussing the results on the performance measures, the non-performance factors invite comment. As was the case in the NBA, shorter female players are at a disadvantage. Other things the same, the taller you are—relative to the average at your position—the better you are going to do in the draft. In contrast to the NBA, age is not important in the WNBA draft sample. This is not surprising given the tight distribution of ages compared to the men when entering the draft. Appearing in the Final Four, however, is important for drafting. A player with this experience will see her draft position improve by almost six slots. In addition, coming out of the ACC, SEC, or the Big East gives a bigger boost than from the PAC 12 or Big Ten.

Turning attention to the performance factors, which of those predicted skills that were statistically significant had the most economic significance? As Table 2 indicates, points scored, assists, and shooting efficiency from the two-point range are all positive influencers of draft position while personal fouls work against the athlete. Steals, blocks, and rebounds are not telling much of the story of draft selection in our sample. Given these predicted results, how meaningful are they?

Table 3 reports how an estimated one standard deviation increase in each statistically significant performance variable impacts draft position. Again, we suspect—given

Table 2. Estimation of Equation (1) (2010-2013)

Variable	Poisson ME	Z-stat	Negative Bin ME	Z-stat
PTS	-0.95***	-9.58	-1.08***	-5.51
REB	-0.05	-0.28	-0.24	-0.63
AST	-2.18***	-7.07	-2.58***	-4.32
STL	-0.41	-0.74	-0.21	-0.19
BLK	-0.52	-1.08	-0.68	-0.71
PF	1.41**	2.67	2.11**	2.04
TOPER	0	0	0	0
3FGPER	4.87**	2.05	3.47	0.78
2FGPER	-50.38***	-5.90	-42.71**	-2.69
FT	-7.09	-1.29	-1.85	-0.17
RELHT	-0.90***	-5.80	-1.18**	-2.73
DFIN4	-5.83***	-4.64	-5.65***	-3.25
AGE	-0.41	-0.62	-0.28	-0.22
DACC	-6.92***	-6.34	-7.32***	-3.48
DPAC12	-3.34**	-2.61	-3.51	-1.39
DBIGEAST	-4.99***	-3.92	-5.79**	-2.51
DSEC	-6.75***	-6.29	-6.60***	-3.13
DBIG10				
DBIG12	-3.95***	-3.22	-4.59**	-1.95
-0.37				
	-3.57	-1.18	-2.47	
DCONFU	3.26	1.10	5.01	0.73
DWEST	3.46*	1.68	2.85	0.68
DCOLON	2.23	0.76	1.89	0.33
DAMER	-2.71	-1.59	-4.08	-1.35
DSUN	1.59	0.64	1.57	1.12
DC	0.78	0.40	1.26	0.32
DF	0.16	0	-0.03	-0.01
DG	-0.16	-0.13	-0.20	0.62

Observations: 128. *Denotes significance at 10%, ** 5%, *** 1%

the aforementioned research into the NBA—that scoring might matter the most. And the results in Table 3 indicate that scoring matters most! A one standard deviation increase in points improves draft position by over eight slots; a similar increase in assists improves drafting by almost five slots and improved field goal percentages improve position by three slots.[14] Relative to the NBA, assists are about twice as valuable in improving draft position in the WNBA while points scored and efficiency are about a third more valuable to the potential professional player.

Table 3. The Impact of a One Standard Deviation Increase in Statistically Significant Performance Variables (2010-2013)

Variable	# slots a player gains from + 1 s.d
PTS	-8.76
AST	-4.95
2FGPER	-2.99
PF	1.60
Observations: 128	

Performance from College to the Pros

Are the factors that impact a college player's draft selection important to subsequent professional performance in the WNBA? Answering this question requires a measure of performance.

Berri (2008) demonstrates how the statistics gathered by the NBA (and thus the WNBA) can be used to estimate a player's Wins Produced.[15] This model of performance proves very reliable season to season and explains about 94% of the variation in team wins. Using this metric we now investigate how each drafted player's Wins Produced per 40 minutes (WP40) might be related to the performance statistics used in the draft model.

Specifically we estimate the following regression:[16]

$$WP40_n = \lambda_0 + \gamma_N PROD + \lambda_1 RELHT + \lambda_2 DFIN4 + \lambda_3 DCHAMP + \lambda_4\, AGE + \lambda_5 DACC + \lambda_6 DPAC12 + \lambda_7 DBIGEAST + \lambda_8 DSEC + \lambda_9 DBIG10 + \lambda_{10} DBIG12 + \lambda_{11} DAMER + \lambda_{12} DCOLON + \lambda_{13} DWEST + \lambda_{14} DCONFU + \lambda_{15} DSUN + \lambda_{16} DC + \lambda_{17}\, DF + \lambda_{18} DG + e_{\,it} \quad (2)$$

where PROD is a collection of player statistics including points, rebounds, steals, blocked shots, assists, and measures of shooting efficiency.

The estimated results for Equation 2—for the first year of a player's WNBA career[17]—are reported in Table 4.

The results indicate that only PTS, PF, 2FGPER, and DC are significant predictors of first-year performance. To provide some sense of the relative influence on WP40 of each of these significant factors an estimated elasticity coefficient is reported, with shooting efficiency found to have the largest impact. This result runs counter to what we found when examining where a player is chosen in the draft. That study noted the primacy of points scored. Although points scored does predict future performance, our results indicate that more attention should be paid to shooting efficiency.

Clearly, given the results in Table 4, where a player is drafted does not reveal very much about her subsequent performance in the WNBA. But "how much" is relative. For an alternative view, consider Table 5, where we consider how much of future performance is explained by where a player is selected.

Table 5 considers two different measures of player performance. The first is WP40. The second is NBA Efficiency.[18] As Berri and Schmidt (2010) note, the former is correlated with team wins but not as correlated with player evaluations in basketball. NBA Efficiency has the opposite properties.

Table 4. How Much Career Performance (WP40) is Explained by Factors Influencing Draft Position?

Variable	1st Year	t-stat	Elasticity
PTS	0.002**	1.97	1.02
REB	-0.001	-0.31	
AST	0.002	0.86	
STL	-0.007	-1.34	
BLK	-0.004	-0.80	
PF	0.008*	1.63	0.53
3FGPER	-0.000	-0.02	
2FGPER	0.224***	2.94	2.86
FT	-0.020	-0.38	
RELHT	-0.001	-0.71	
DFIN4	0.008	0.78	
AGE	-0.002	-0.36	
DCONF	-	-	
DC	-0.32*	-1.85	
DF	-0.010	-0.87	
DG	0.052	1.03	
obs	80		
R-squared	0.23		

* denotes significance at 10%, ** 5%, *** 1%

As Table 5 notes, only about 6% of a player's career performance as captured by WP40 is explained by where a player is drafted. Explanatory power increases when NBA Efficiency is used to measure performance. Of course—as noted in Berri and Schmidt (2010)—NBA Efficiency is a poor measure of player productivity.

We should note that similar results held in the work done by Berri et al. (2011) with respect to the NBA draft. This confirms the strange result that—armed with more information (in-person observations of the player in action and other qualitative data)—decision-makers do not predict professional performance very well. Our model of college performance measures seems to predict future performance better than that used by the teams. Furthermore, management seems to be evaluating female and male players in a similar fashion. Any bias in the hiring process is clearly linked to points scored by the player; NBA and WNBA executives alike tend to overemphasize this statistic. Even though this research does not directly test for gender neutrality it hints indirectly at it. The absolute dollar value of poor decisions is obviously lower in the WNBA than in the NBA. Still, important consequences exist for decision-makers. Losing coaches tend to be fired. Given the short supply of tall productive players it is reasonable to imagine most teams want to make judicious draft decisions. In this regard, if these choices reflect the sum of collective wisdom of the team management, the draft does not seem to really accomplish its intended purpose.

Table 5. How Much Career Performance Can Draft Position Explain (as captured by WP40 and NBAEfficiency)

Year	Observations	WP40	NBAEfficiency
1^{st} Year out	80	-0.051***	-7.300***
R-squared		0.06	0.14

Concluding Observations

This research on the draft in the WNBA confirms prior results in the NBA with respect to performance predictions. Specifically it shows that teams appear to consistently rely on faulty indicators when making draft picks. For example, factors like Final Four experience, conference affiliation, and relative height influence draft selection but fail to accurately predict the players' performance in the WNBA. In contrast to studies of NBA performance, rebounds, steals, and turnovers are not an important part of the story for draft selection in the WNBA. This result could be a function of our smaller sample size, but may also be indicative of a different type of play on the court. With more data this is certainly another potential line of inquiry to pursue.

Since evidence of gender bias has been found in a variety of studies, these results could be important in this field as well. If the performance of female basketball players is evaluated the same way male performance is then additional studies into other sports might provide a new laboratory for those interested in measuring productivity and marginal revenue product.

Given the above, female college basketball players can benefit from two pieces of advice aside from standing up as tall as possible when their height is officially measured: (1) score as many points as you can during your college career and (2) do whatever you can to make sure that career occurs in the SEC, ACC, or Big East. For the time being, it looks like that's what matter most to WNBA teams when they make their draft decisions.

References

Basketball Reference. (n.d.). Retrieved from http://www.basketball-reference.com

Bertrand, M., & Hallock, K. (2001). The gender gap in top corporate jobs. *Industrial and Labor Relations Review, 55*, 3-21. Retrieved from http://digitalcommons.ilr.cornell.edu/hrpubs/14/

Basow, S. A. (1995). Student evaluations of college professors: When gender matters. *Journal of Educational Psychology, 87*, 656-665.

Berri, D. J. (2005). Economics and the National Basketball Association: Surveying the literature at the tip-off. In J. Fizel (Ed.), *The handbook of sports economics research* (pp. 21-48). London, UK: M.E. Sharpe, Inc.

Berri, D. J. (2010). Measuring performance in the National Basketball Association. Working paper.

Berri, D. J., Brook, S., & Fenn, A. (2011). From college to the pros: Predicting the NBA amateur player draft. *Journal of Productive Analysis, 35*, 25-35.

Berri, D. J., Brook, S. L., & Schmidt, M. B. (2007). Does one simply need to score to score? *International Journal of Sport Finance, 2*, 190-205.

Berri, D.J., Brook, S., Fenn, A., Frick, B., & Vicente-Mayoral, R. (2005). The short supply of tall people: Explaining competitive imbalance in the National Basketball Association. *Journal of Economic Issues, 39*, 1029-1041.

Berri, D. J., & Krautmann, A. C. (2013). Understanding the WNBA on and off the court. In M. Leeds & E. S. Leeds (Eds.), *Handbook on the economics of women in sports* (pp. 132-155). Cheltenham, UK: Edward Elgar Publishing.

Berri, D. J., & Schmidt, M. B. (2010). *Stumbling on wins: Two economists explore the pitfalls on the road to victory in professional sports*. Princeton, NJ: Financial Times Press.

Berri, D. J., Schmidt, M. B., & Brook, S. L. (2006). *The wages of wins: Taking measure of the many myths in modern sport*. Palo Alto, CA: Stanford University Press.

Berri, D. J., & Simmons, R. (2011). Catching a draft: On the process of selecting quarterbacks in the National Football League amateur draft. *Journal of Productive Analysis, 35*, 37-49.

Coates, D., & Oguntimein, B. (2010). The length and success of NBA careers: Does college production predict professional outcomes? *International Journal of Sport Finance, 5*, 4-26.

Gourieroux, C., Monfort, A., & Trognon, A. (1984). Pseudo-maximum likelihood methods: Applications to poisson models. *Econmetrica, 52*, 701-720.

Hollinger, J. (2003). Pro basketball prospectus: 2003-2004. Washington, DC: Brassey's Inc.

Humphreys, B. (2000). Equal pay on the hardwood: The earnings gap between NCAA Division I basketball coaches. *Journal of Sports Economics, 1*, 299-307.

Kahn, L. M., & Sherer, P. D. (1988). Racial differences in professional basketball players' compensation. *Journal of Labor Economics, 6*, 40-61.

Marlowe, C. M., Schneider, S. L., & Nelson, C. E. (1996). Gender and attractiveness biases in hiring decisions: Are more experienced managers less biased? *Journal of Applied Psychology, 81*, 11–21.

Massey, C., & Thaler, R. H. (2006). The loser's curse: Overconfidence vs. market efficiency in the National Football League draft. NBER Working Paper, (W11270).

NCAA statistics. (n.d.). Retrieved from http://www.ncaa.com/stats/basketball-women/d1

Oliver, D. (2004). *Basketball on paper*. Washington, DC: Brassey's Inc.

Quinn, K. G. (2008). Player drafts in the major North American sports leagues. In B. R. Humphreys & D. Howard (Eds.), *The business of sport*, Vol. 3. Westport, CT: Praeger Publishers.

Staw, M. M., & Hoang, H. (1995). Sunk costs in the NBA: Why draft order affects playing time and survival in professional basketball. *Administrative Science Quarterly, 40*, 474-494.

Taylor, B. A., & Trogdon, J. B. (2002). Losing to win: Tournament incentives and the draft lottery in the National Basketball association. *Journal of Labor Economics, 20*, 23-41.

Treme, J., & Allen, S. (2009). Widely received: Payoffs to player attributes in the NFL. *Economics Bulletin, 29*, 1631-1643.

Weir, K., & Wu, S. (2014). Criminal records and the labor market for professional athletes: The case of the National Football League. *Journal of Sports Economics, 15*, 617-635.

WNBA official website. (n.d.). Retrieved from http://www.wnba.com

Endnotes

[1] A sample of this literature would include Coates D, Oguntimein B (2010) and Berri, DJ, Brook S, Fenn A, (2011).

[2] The league began play in 1997. Recent notable events include the Shock relocating from Detroit to Tulsa, a league-wide multiyear marketing partnership with Boost Mobile landing a logo on jerseys of 10 out of the 12 teams,; and in April of 2011, the appointment of Laurel J. Richie as President of the league.

[3] The Noll-Scully measure of competitive balance ranges between 1.1 to 2.6 for 1997 to 2013 for the WNBA; with an average value of 1.9 In comparison, the NBA – from 1997-98 to 2013-14 – had a range of 2.3 to 3.4 with an average value of 2.8. Berri and Krautmann (2013) discuss potential reasons for this difference.

[4] Much of this talent is found in the college ranks for the NBA and NFL. For MLB and NHL, high school talent is also considered. The WNBA also primarily drafts from the college ranks. And like the NBA, the top picks in the draft are assigned via a lottery. Rookies may only sign a three year, non-guaranteed contract with an option in favor of the team for a fourth year.

[5] The Berri, Brook, and Fenn (2011) paper looked at drafts from 1995 to 2009. A similar argument with respect to college scoring was also made by Coates and Oguntimein (2011) in a study of drafts from 1987 to 1989. For research on other character traits like criminal violations and draft order see Weir and Wu (2014). Treme and Allen (2009) find faster more accomplished football players are drafted earlier but 40 yard dash times are not correlated with professional performance in early career years.

[6] These authors also cite research that scoring dominates the allocation of minutes and voting for post-season awards (by coaches and the media).

[7] For the 2013 season minimum salaries ranged from $37,950 to $55,000 and maximum salaries range from $105,000 to $107,500. Many players supplement their income by playing in international leagues in the off –season.

[8] See for example Bertrand and Hallock (2001), Humphreys (2000) or Marlowe Schneider and Nelson (1996)

[9] This approach follows the lead of Berri, Brook, and Fenn (2011).

[10] The -1.57 minimum for blocks occurs due to the position adjustment process. If the "'worst" blocker in our sample performs well below the average for her position it is possible for the position adjustment to return a negative value. See footnote 12 for a full description of how position adjustments are made.

[11] Position bias is overcome by calculating a position adjusted value for each metric. Each player's per-minute performance with respect to points, rebounds, steals, blocked shots, assists, and turnovers is determined. Then, the average per-minute accumulation at each position in our data set is subtracted. The average value of the statistic across all positions is added back in. After these steps, the result is multiplied by 40 minutes (the length of a college game), to return the player's per 40 minutes production of each statistic.

[12] Relative height is determined by calculating the average height—in inches—of the drafted players in the sample at each position. The position average is then subtracted from each player's height. The average height in the entire sample is then added back in.

[13] As discussed in Berri, et al (2011) we adopted a two-step negative binomial quasi-gneralized pseudo-maximum likelihood estimate to correct for overdispersion and to generate a robust variance-covariance matrix. More information on this estimator can be found in Gourieroux, et al. (1984).

[14] Note that for an increase in personal fouls of one standard deviation draft position will decrease by a little over 1 slot.

[15] This model was updated for Berri and Schmidt (2010). Details can be found at http://wagesofwins.com/how-to-calculate-wins-produced/

[16] This is equation (1) with WP40 as the dependent variable (instead of Pick).

[17] Relative to the aforementioned work of Berri, Brook and Fenn on the NBA draft, our sample for the WNBA study is quite small.

[18] NBA Efficiency is calculated as follows: PTS + TREB + STL + AST + BLK – All missed shots – Turnovers. As Berri and Schmidt (2010) note, this model does not explain wins very well. That is because it de-emphasizes shooting efficiency. But it does a good job of explaining player evaluation in the NBA (primarily because the NBA decision-makers tend to de-emphasize shooting efficiency).