

# **Do Advanced WNBA Defensive Stats Predict Making the All-Defensive Team Chosen by the Coaches?**

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**INTRO:** In basketball a made shot is an easily measurable offensive measure, but individual defensive metrics are harder to quantify. To address that, Defensive Rating (a measure of how many points per 100 possessions are allowed when that player plays) and Defensive Win Shares (how many wins the player added based on their defensive play) were created. But do they align with what coaches judge as good individual defenders?

**METHODS:** As a proxy for how coaches evaluate defenders, I chose WNBA All-Defensive first and second teams selected by the league head coaches. Quantitative metrics were taken from [www.stats.wnba.com](http://www.stats.wnba.com) for the 2018 and 2019 seasons for players with more than 250 minutes. I ran a binary logistic regression to see whether or not Defensive Ratings or Defensive Win Shares significantly increased the odds of being on the All-Defensive First or Second Teams.

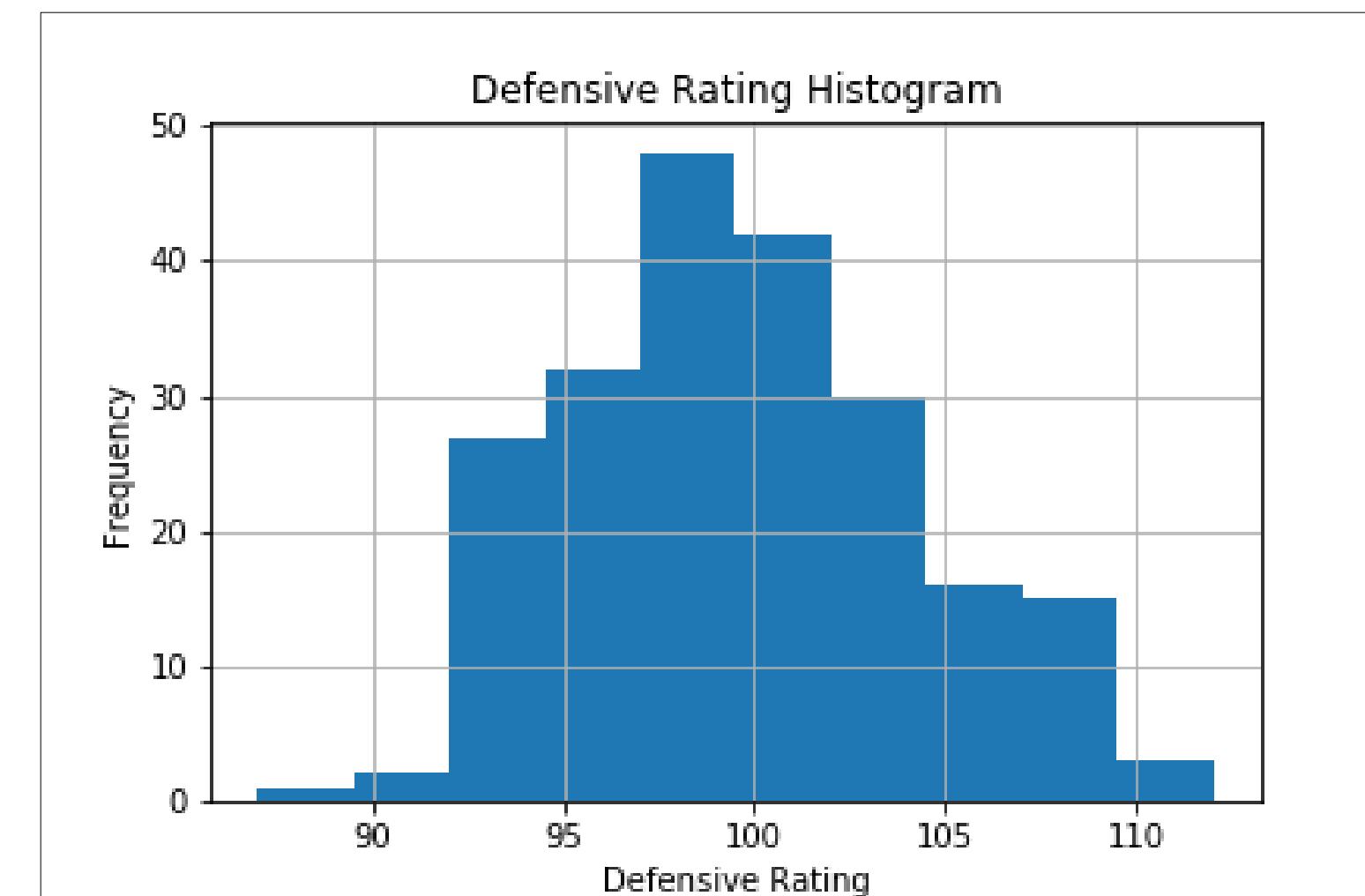
**RESULTS:** Players with a Defensive Rating under 100 had statistically significantly better odds of being on one of the All-Defensive teams, as did players with more than 3 Defensive Win Shares. Thus, the quantitative measures appear to align with the qualitative opinion of the coaches. At least for the top ten players. This is an encouraging development in measuring defensive impact and bodes well for the future of basketball analytics. Perhaps in the future teams can follow the lead of baseball and devise analytic based defensive strategies.

# Players rated well defensively by the numbers have better odds of being chosen as top defenders by the coaches.

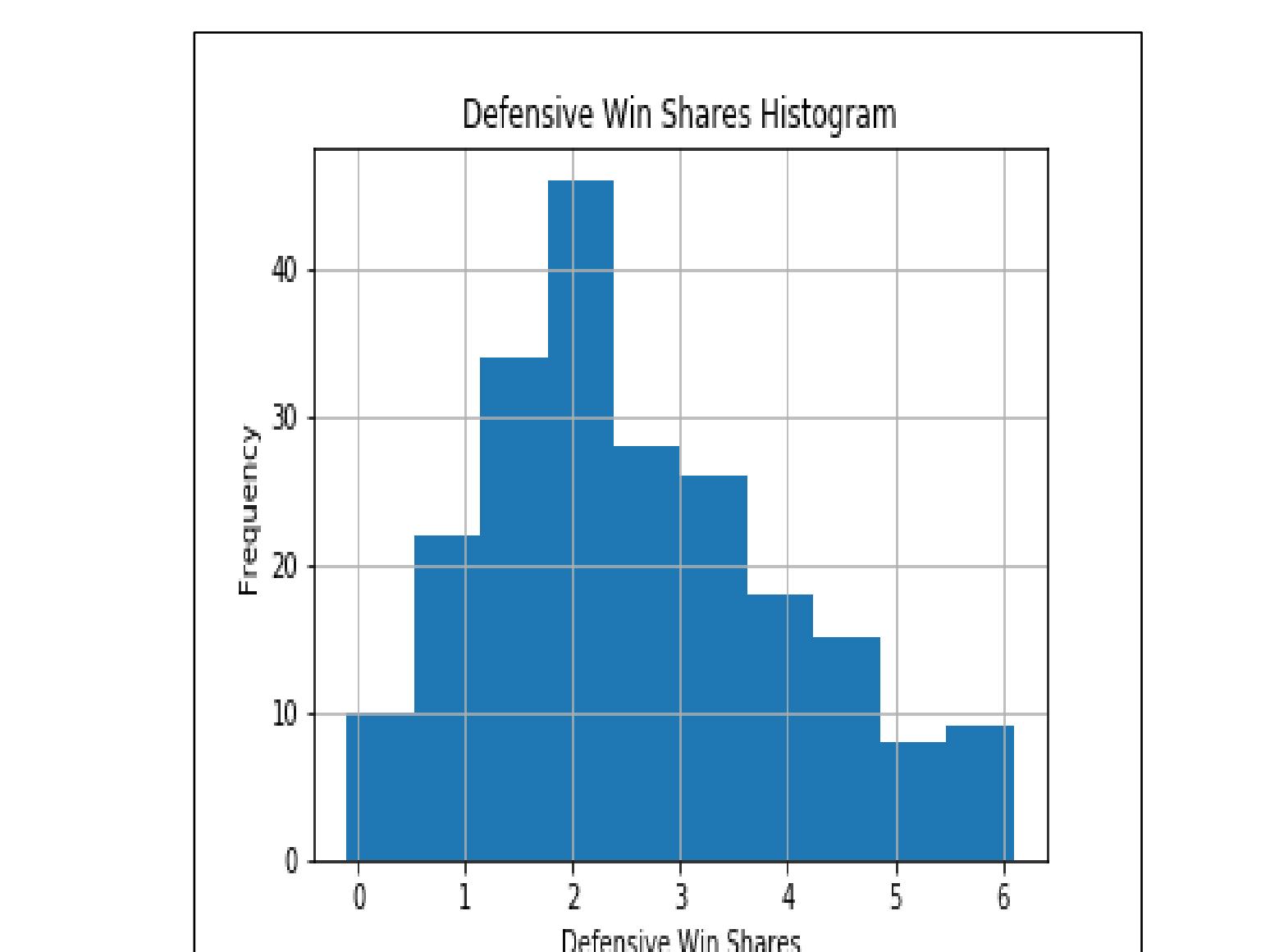
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Optimization terminated successfully. Current function value: 0.282445 Iterations: 14 Function evaluations: 15 Gradient evaluations: 15 Results: Logit						
Model: Logit Pseudo R-squared: 0.084 Dependent Variable: All Defense AIC: 126.0162 Date: 2019-10-30 22:34 BIC: 132.7667 No. Observations: 216 Log-Likelihood: -61.068 DF Model: 1 LL-Null: -66.635 DF Residuals: 214 LLR p-value: 0.06079457 Converged: 1.0000 Scale: 1.0000						
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Coef. Std.Err. z P> z  [0.025 0.975] Under100 1.8368 0.6424 2.8594 0.0042 0.5778 3.0958 constant -3.5362 0.5857 -6.0374 0.0000 -4.6841 -2.3882						
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2.5% 97.5% OR Under100 1.782060 22.104527 6.276273 constant 0.009241 0.091796 0.029125						



Optimization terminated successfully. Current function value: 0.230987 Iterations: 14 Function evaluations: 15 Gradient evaluations: 15 Results: Logit						
Model: Logit Pseudo R-squared: 0.251 Dependent Variable: All Defense AIC: 103.7865 Date: 2019-10-30 22:33 BIC: 110.5370 No. Observations: 216 Log-Likelihood: -49.893 DF Model: 1 LL-Null: -66.635 DF Residuals: 214 LLR p-value: 7.1869e-09 Converged: 1.0000 Scale: 1.0000						
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Coef. Std.Err. z P> z  [0.025 0.975] Over3 3.2691 0.7632 4.2831 0.0000 1.7731 4.7650 constant -4.2908 0.7120 -6.0260 0.0000 -5.6863 -2.8952						
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2.5% 97.5% OR Over3 5.889156 117.338621 26.286467 constant 0.003392 0.055289 0.013695						



[www.danoff.org/ball](http://www.danoff.org/ball)

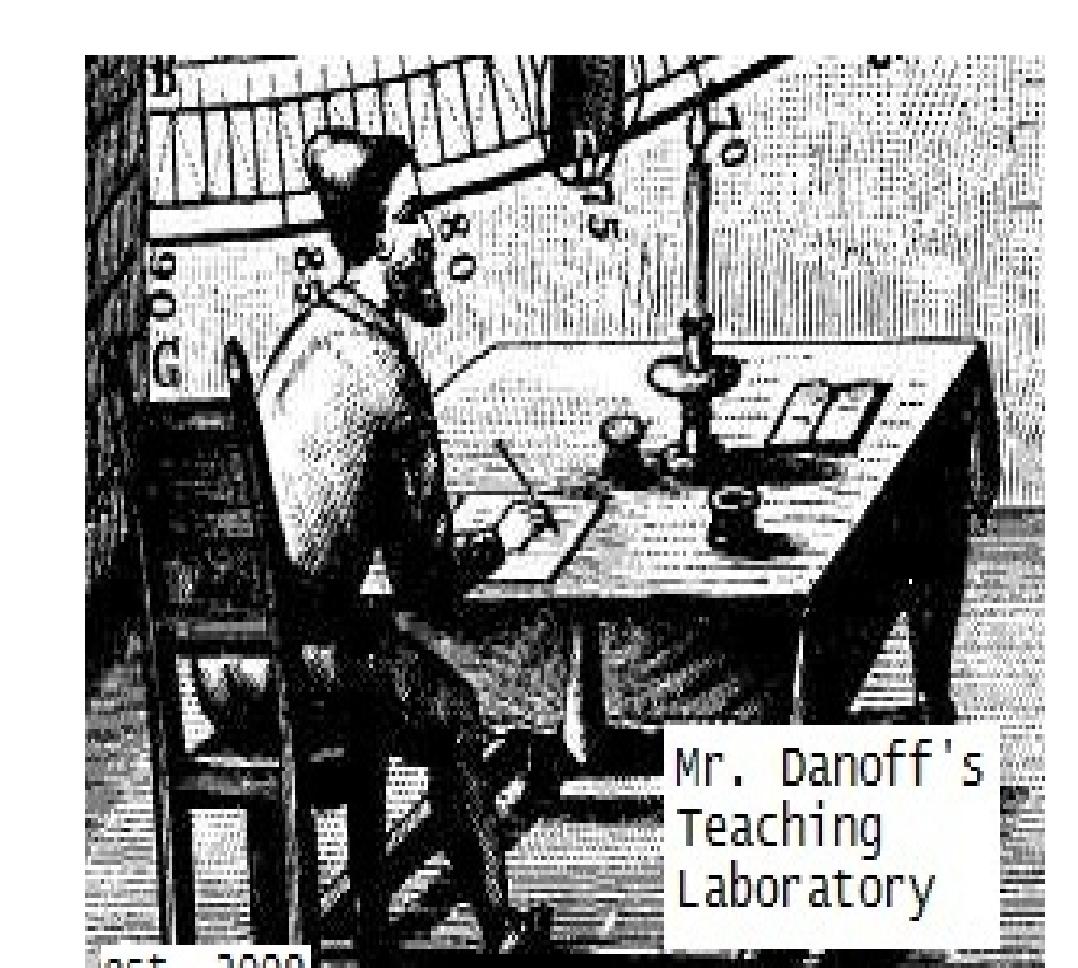


Photo of Rebekkah Brunson guarded by Nneka Ogwumike "Brunson 20161009" by Susan Lesch via Wikimedia Commons. Available Under the Creative Commons 0 Dedication. [https://commons.wikimedia.org/wiki/File:Brunson\\_20161009.jpg](https://commons.wikimedia.org/wiki/File:Brunson_20161009.jpg)