The Value of Tanking in the NFL

Introduction and Purpose of Study

As stated by Chicago White Sox General Manager Rick Hahn, “You don’t want to be a club that’s not good enough [to win] a championship but at the same time is just stuck in the middle” (Sheinin). As a result, teams in professional sports, namely the NBA, often lose games on purpose in order to secure a higher draft pick. With the higher draft pick, teams have a better selection regarding who they want to draft and often end up with a better player relative to a lower draft selection (Kram). The thought process here is that a better player will make the team better, driving them “over the hump” of a mediocre record into championship contention.

In the NFL, tanking has been less prevalent, but teams have allegedly started to engage in the practice. In January 2022, Brian Flores, former head coach of the Miami Dolphins, filed a class-action lawsuit stating, among other things, that, “Miami’s owner, Stephen Ross, told Mr. Flores that he would pay him $100,000 for every loss, and the team’s general manager, Chris Grier, told Mr. Flores that ‘Steve’ was ‘mad’ that Mr. Flores’ success in winning games that year was ‘compromising (the team’s) draft position” (Inabinett). Although the claims have not yet been substantiated, the concept of tanking is familiar to fans of the NFL, and teams are considering the approach.

There has been no formal research on the effect of tanking in the NFL in general. This study aims to find the value of winning in the NFL as well as the value of obtaining a higher draft selection if there is any. With the knowledge of these values, teams may be better equipped to determine whether or not they should purposely lose games. Through the use of data analysis techniques and public data, this paper aims to determine the effect of tanking on the wins of an NFL team each year for five years into the future.

Description of Data & Method Used

In order to model the effect of tanking on winning, there are two models that I used. First, I used a collection of models to predict a team's win percentage (WP) from a player's AV (Approximate Value). Then, I used another collection of models, based on the first one, to predict a player's WAR (Wins Above Replacement) from their draft position. The main goal of tanking is to obtain a better draft selection, so draft selection should be an appropriate input to attempt to predict the effect of tanking on wins. However, it should be noted that football is a team sport, relying on 11 players at a time, with hundreds of coaches and staff members assisting them. As such, it is impossible to fully analyze the true effect of one specific player on the field. Furthermore, some positions carry more weight than others; for example, the quarterback of each team is often responsible for calling plays, and handles the ball on every pass attempt, causing them to have more control over a game's outcome. This means different positions on the field should be weighted differently when calculating their effect on games.

In this study, I decided to solely use first-round draft selections because the difference between draft picks diminishes over time. According to a previous study by Massey and Thaler (2013), the performance value of a player drops by approximately $2 million from the 1st to 32nd pick, which is more than the difference in value between the 32nd pick and the last pick in the draft. Therefore, as the value of draft picks diminishes over time, the difference in wins from first-round players should account for the majority of the effects of tanking.

Next, Approximate Value (AV) is a metric developed by Pro Football Reference. AV utilizes a large number of public statistics and converts them into a single number, dependent on factors such as yards, award recognition, and position. Although there are many different factors that go into determining the AV of a player, this metric is publicly available and condenses each player's season into a single number.

Ultimately, team management cares about wins; although AV may be helpful in evaluating individual player performance, teams tank to win more, not to simply obtain the highest AV player. Depending on the results of the first models, even if the difference in AV is high between each pick, if that does not correlate to a high winning percentage, then the benefits of tanking may be lower than expected. Using AV, I predicted the win percentage of a team. The exponential regression model for each position group is as follows:

$$WP_i = m * e^{(-t * AV)} + b$$

Here, WP_i represents the win percentage of a team in year i, and AV_i represents the AV of a player in year i. I decided to use win percentage here because the NFL recently changed the number of games a team plays in a year from 16 to 17, so a win percentage estimate (relative to wins) helps to standardize that metric. I chose to use an exponential regression model here because, first, as AV goes up, win percentage should also increase; any model that goes against that would be overfitting and accounting for outliers.

It is important to note that I applied this model to each position group. This is because different positions may have different correlations between AV and WP. Based on the positions available in nflfastR's roster database, I separated the players into position groups as follows: OL (offensive line), DB (defensive back), DL (defensive line), LB (linebacker), RB (running back), ST (special teams), QB (quarterback), TE (tight end), and WR (wide receiver).

Moreover, I decided to use an exponential regression model over a linear regression model because the r^2 value of the exponential regression model was approximately 20% higher than the linear regression one. Furthermore, it makes logical sense that the difference between the best and second-best players would mean more than the difference between two average players.

I obtained both the AV and win percentage data from Pro Football Reference. The data are from 2000-2021. Now, we can model the win percentages from AV. Using the model listed, I created a win percentage prediction from each AV from each first-round pick in their first five years in the National Football League. Then, using that data, I was able to model the correlation between a draft selection and a team's win percentage.

Because players progress over time, it would not make sense to evaluate whether or not a player is successful over a single year, especially the first. Furthermore, a model should not expect that, given a specific draft position, a player in that position would have the same value for their first five years. Therefore, I created five exponential regression models to predict the WAR of a player from their draft position for each of their first five years in the NFL. For my model, WAR refers to the predicted wins a team with that player would get relative to if they had a winning percentage of 50% (average). These models are as follows:

$$WAR_1 = m * e^{(-t * x)} + b$$

$$WAR_2 = m * e^{(-t * x)} + b$$

$$WAR_3 = m * e^{(-t * x)} + b$$

$$WAR_4 = m * e^{(-t * x)} + b$$

$$WAR_5 = m * e^{(-t * x)} + b$$

Here, WAR represents a pseudo WAR statistic, and x represents the draft selection of a team. WAR_i corresponds to the WAR for a player's ith year in the league. I chose to implement an exponential model because, first, it would not make sense to implement a model where the slope is negative, i.e.when pick increases, WAR should decrease; a higher value pick should, in general, correspond to a better player. Next, I decided to use an exponential model over something such as a linear regression model because the value between picks can change over the course of the first round. For example, the difference between the 1st and 5th pick could be significantly more important than the difference between the 28th and 32nd pick. I decided to model the correlation between draft pick and WAR instead of AV, making WAR the dependent variable, because the results would then be more easily comparable to other WAR statistics discussed later.

To obtain the data of the picks of players, I used a database from Lee Sharpe. I took data from the years 2000-2017.

Another metric to predict wins in a given season is provided by the paper, "nflWAR: a reproducible method for offensive player evaluation in football" (Yurko, Ventura, & Horowitz). This metric applies to skill position players on offense (quarterbacks, running backs, wide receivers, & tight ends), so it could not be applied to all players. However, I adapted their findings to calculate WAR for skill position players from 2006-2021. I was unable to take statistics from before that time frame because some statistics used in the WAR calculations were not tracked at that time. Throughout this paper, I will use both the win percentage predicted from AV as well as this WAR statistic for skill position players to analyze the differences in their predictions and the effects that more advanced WAR statistics may have on data.

It is important to note that wins are not predictive of value for an NFL team using public data. Based on prior research that aimed to find a correlation between winning and value in the

NBA (Araque et al.), I aimed to create a similar model to predict the value of winning in the NFL. I used a model to predict growth as follows:

$$GROWTH_i = \beta_1 POP_i + \beta_2 GDP_i + B_3 HOMES_i + B_4 WL_i + VALUE_i$$

Here, growth represents the difference, in billions of dollars, between a team's previous value and their next one. POP is the team's city population, GDP is the team's city GDP, HOMES is the team's metro area Nielsen households, WL is the team's previous win-loss percentage, and VALUE is the team's previous value, in billions.

First, I used population, GDP, and the amount of Nielsen homes in a team's area to determine if market size was a moderating variable. Next, I included a team's previous value as it accounted for over 98 percent of the variation in the value in year i+1, helping to account for the fact that a team's growth may be affected by its previous value.

With the base model, using no filters or adjustments, the p-value for the correlation between the win percentage of a team in year i relative to their value in year i+1 was over 0.2, so the correlation was not statistically significant (<0.05).

Using each of these variables, I separated the data into quartiles and determined the effect of a winning percentage on growth in each quartile. This may explain some moderating variables, where winning percentage may matter more for certain markets or values. In each quartile of population, GDP, Nielsen homes, and previous value, however, the model did not yield a p-value lower than the standard error of 5% for the WL variable using this formula, outside of two outliers which predicted that wins were inversely related to team value. I also attempted to substitute growth in percentage for the GROWTH variable but attained similar results.

Similar to prior research done on the NBA (Araque et al.), I attempted to standardize growth from average with the following formula:

GrowthFromMean = GROWTH - MEANGROWTH

Here, GROWTH is a team's growth (in %) in a specific season and MEANGROWTH is the average growth for a team in the same tercile of population/GDP/Nielsen homes in that same year for each of the three variables listed. I attempted to predict GrowthFromMean using the same model; in the statistically significant correlations between past wins and this variable, these models calculated each win to have around 0.003 of a billion dollars or less added in value per win, which is not significant.

As a result, this paper does not recommend a team to tank or not based on team value, as there is no statistical significance to the hypothesis that winning increases team value in the NFL.

This conclusion is supported by research that states that although winning is heavily correlated with franchise value in both the NBA (National Basketball Association) and MLB (Major League Baseball), the NFL does not have a statistically significant relationship between winning and franchise value. Media deals and sharing of gate receipts in the NFL are plausible explanations for this discrepancy (Geckil).

With regards to the data, I used Forbes's NFL values from 2009-2022 to calculate previous value and growth, US Census data to determine the population of each area, data from the Bureau of Economic Analysis to find the GDP of each metropolitan area, data from Lyons

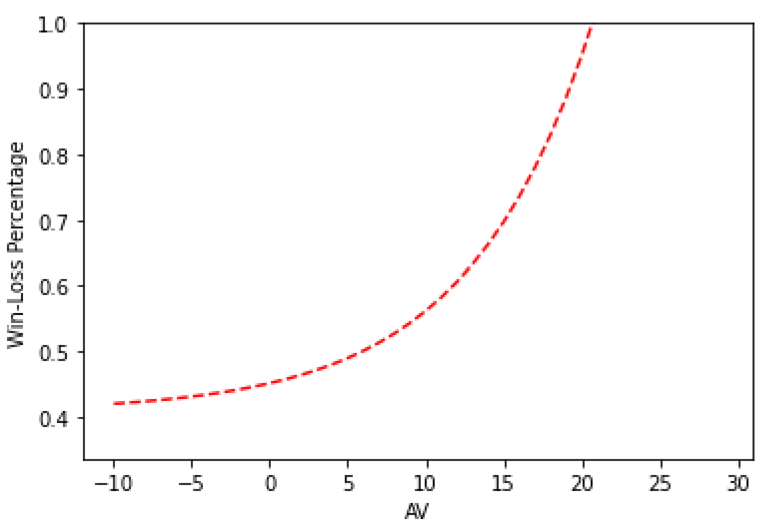
Public Relations to locate the amount of Nielsen Homes per market area, and data from Pro Football Reference to find the win-loss percentage of each team for each year.

Results

Shown below are each model's predictions for each AV from -10 up to a win percentage of 100% or AV of 30. Outside of the special teams (ST) position group (which had a p-value of over 0.9), each model had a p-value of approximately 0.00, so there is approximately a 100% chance that changes in the response (win percentage) are associated with a change in the predictions of the model. Due to there only being one special teams player drafted in the first round from 2000-2019, I removed that observation from my model.

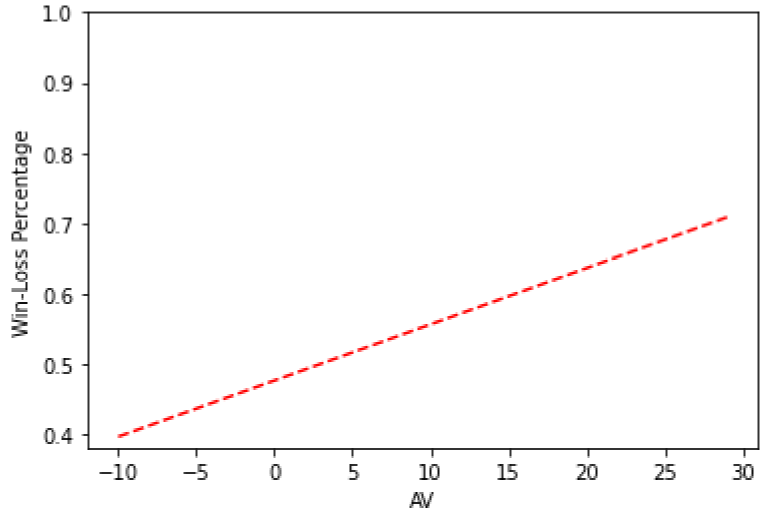
Offensive Line:

$$WP_i = 0.0437 * e^{(0.126 * AV)} + 0.4080$$



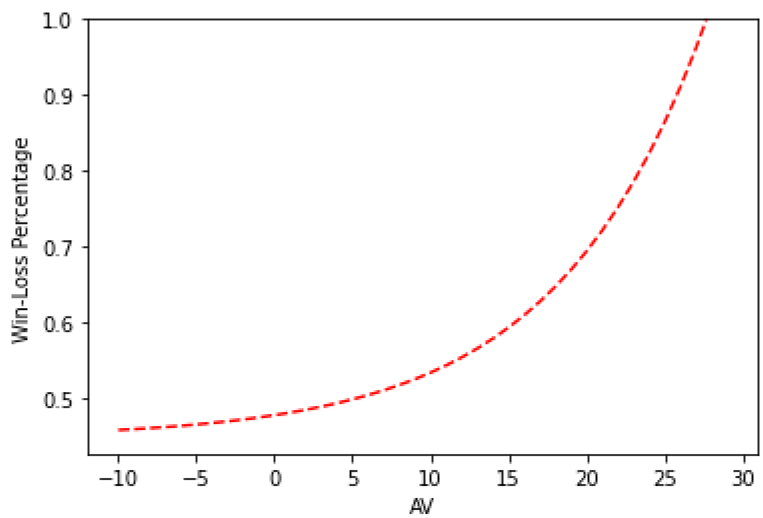
Defensive Back:

$$WP_i = -335.589 * e^{(-0.000024 * AV)} + 336.066636$$



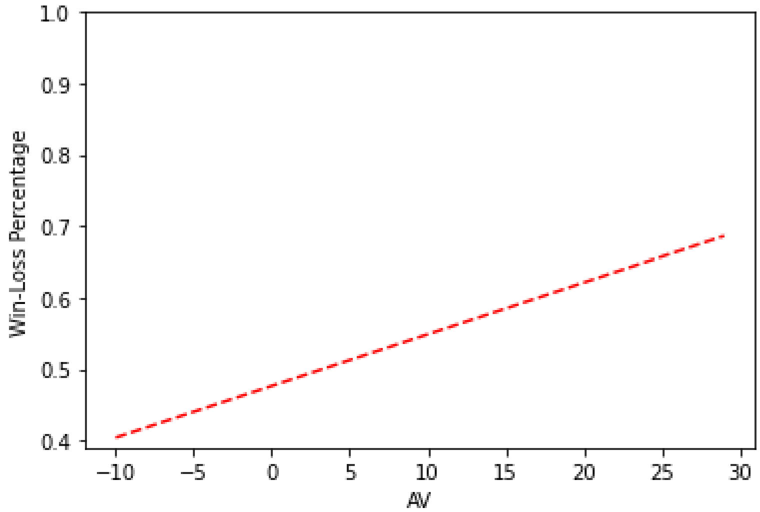
Defensive Line:

$$WP_i = 0.030175 * e^{(0.105 * AV)} + 0.4477$$



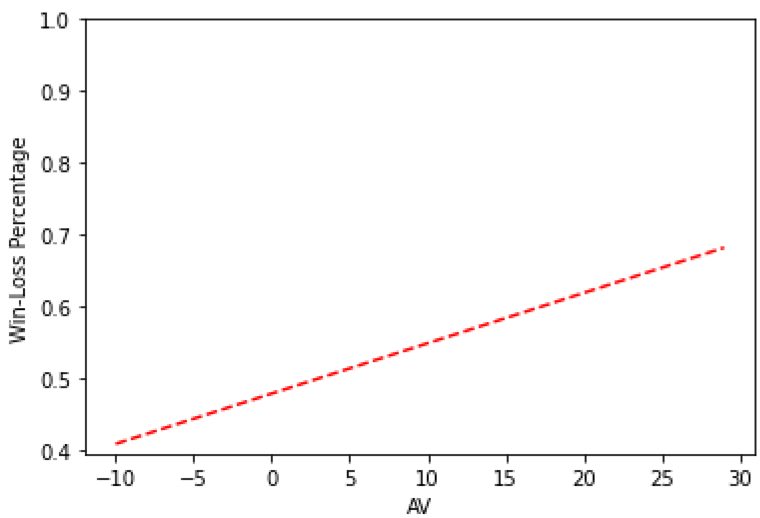
Linebacker:

$$WP_i = -369.484 * e^{(-0.00002 * AV)} + 369.96$$



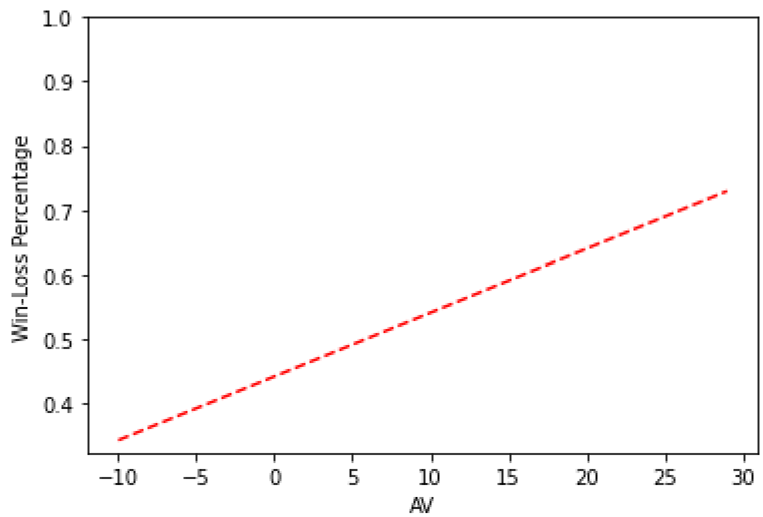
Running Back:

$$WP_i = -313.333 * e^{(-0.000022 * AV)} + 313.813$$



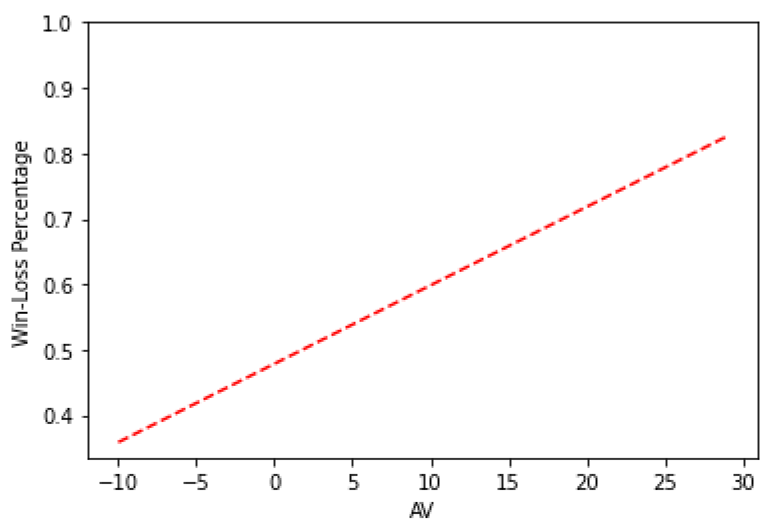
Quarterback:

$$WP_i = -1044.9733 * e^{(-0.000009 * AV)} + 1045.415$$



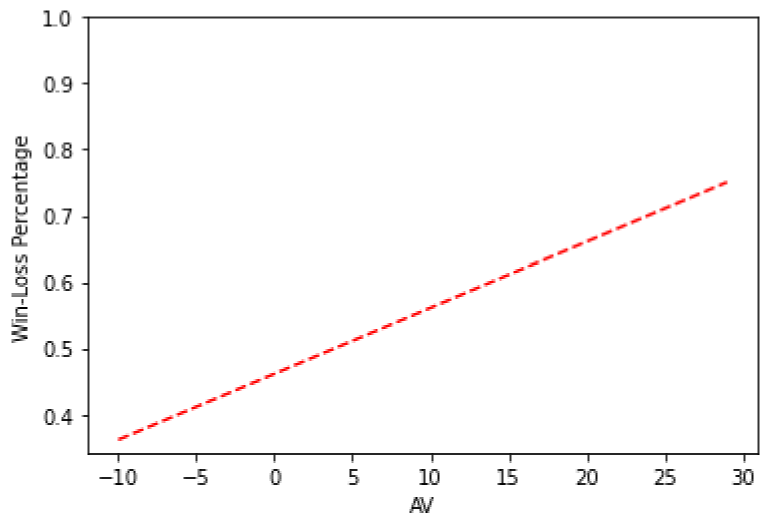
Tight End:

$$WP_i = -515.293 * e^{(-0.000023 * AV)} + 515.772$$



Wide Receiver:

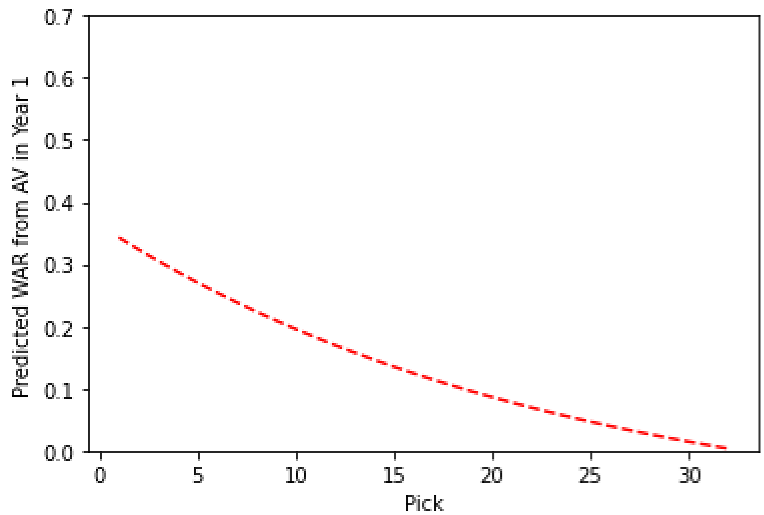
$$WP_i = -585.797 * e^{(-0.000017 * AV)} + 586.259$$



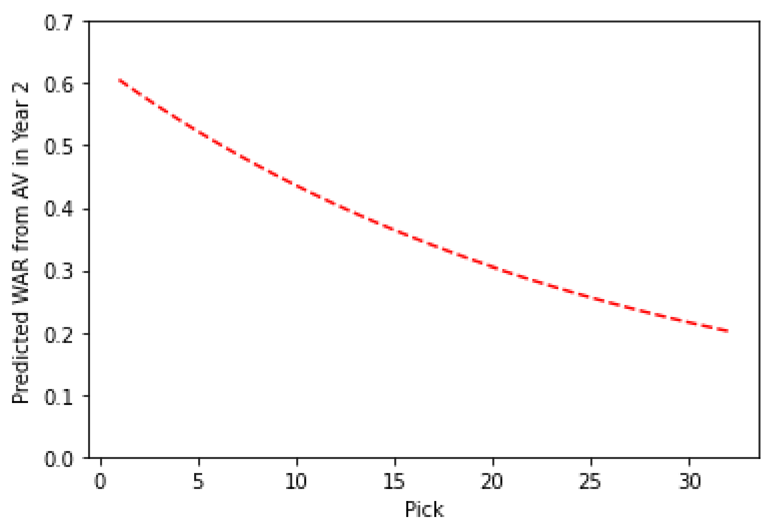
The mean AV of players was around 3.46 from 2000-2021. The minimum Approximate Value of a player in a single season in this timeframe is -5, achieved by Ryan Lindley of the Cardinals in 2012 and Mike Glennon of the Giants in 2021. The maximum AV of a player in a season is 26, accomplished by Ladanian Tomlinson in his 2006 season that earned him the Most Valuable Player award.

Next, the following are the results for the draft pick to pseudo-WAR models for the first five years of a player's career, where x represents the draft pick and WAR_i represents the WAR of a player in their ith year in the league:

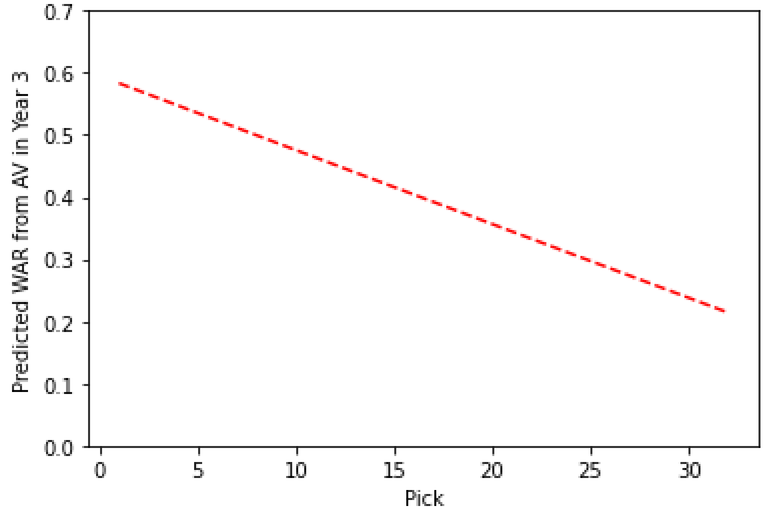
$$WAR_1 = 0.4844 * e^{(-0.0424 * x)} + -0.1212$$



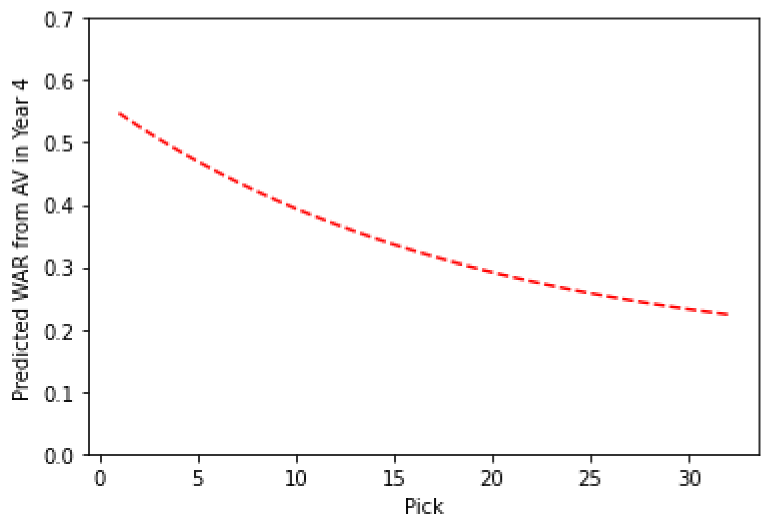
$$WAR_2 = 0.601 * e^{(-0.03874 * x)} + 0.028$$



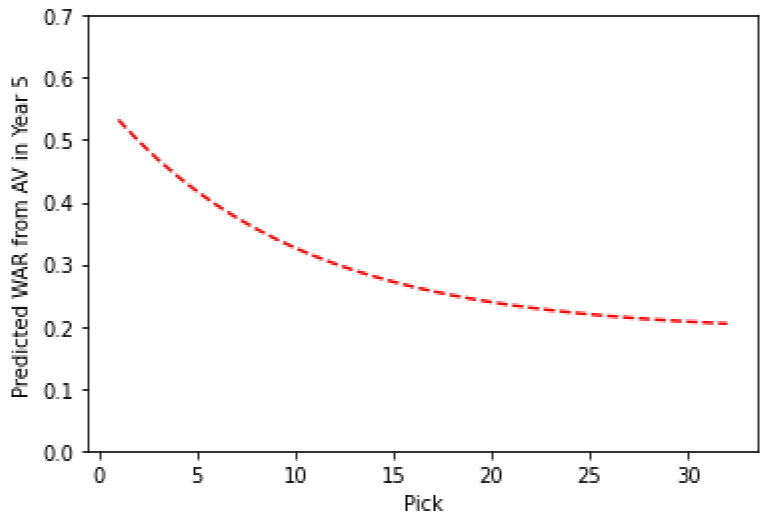
$$WAR_3 = 34.003 * e^{(-0.0003 * x)} + -33.408$$



$WAR_4 = 0.4193 * e^{(-0.0543 * x)} + 0.1502$



$WAR_5 = 0.3792 * e^{(-0.1025 * x)} + 0.1902$



Each model had a p-value of 0.005 or less, so there is approximately a 100% chance that a change in the response (WAR) is associated with a change in the model. There were 571 observations recorded.

Using these results, Table 1 depicts the predicted WAR difference between picks 1-16 and picks 1-32. I chose picks 1-16 as the first range because a mediocre team would be the most likely to tank; they are not good enough to be in playoff contention, so they would not increase their chances of winning a championship by winning a few extra games.

Table 1: Draft Pick to WAR (AV Model)

	WAR Difference from Pick 1-16	WAR Difference from Pick 1-32
Year 1	0.218645	0.339725
Year 2	0.254634	0.403909
Year 3	0.179138	0.369178
Year 4	0.221279	0.323373
Year 5	0.268701	0.327972
Mean	0.228479	0.352832
Total	1.142397	1.764158

Overall, a team tanking from pick 16 to pick 1, approximately losing more than 6 extra games, would only stand to gain an extra 0.23 wins each year, or 1.14 wins total over the next five years combined. From the 32nd overall pick to the 1st, a team would only gain approximately 0.35 wins each year in terms of AV, and 1.76 games over the next five years combined.

However, it is to be noted that many teams will primarily tank for a quarterback, arguably the most important position in sports. Applying similar exponential models to solely predict quarterback WAR, I obtained the following table:

Table 2: Draft Pick to WAR (AV Model) for QBs

	WAR Difference from Pick 1-16	WAR Difference from Pick 1-32
Year 1	0.622132	0.646950
Year 2	0.379060	0.578511
Year 3	0.418436	0.864651
Year 4	0.235200	0.486018
Year 5	0.667644	0.699084
Mean	0.464494	0.655043
Total	2.322472	3.275215

Here, a team tanking from pick 16 to pick 1 would only win approximately 0.46 more games a year relative to if they did not tank each year for the next five years, or 2.32 games combined over the five years. Going from the lowest to the highest value pick in the first round, a team would only win approximately 0.66 more games a year, or 3.28 games total over the next five years combined using this model.

In terms of the WAR statistic developed by Yurko, Ventura, & Horowitz, I attempted to apply a similar exponential regression model to predict each year of WAR relative to draft selection. However, all p-values for linear regression were over 0.1, and relative to the exponential model, the only p-value below a significance level of 0.05 predicted WAR increasing as pick number increased. The number of samples for these models was 112, taken from first-round skill position draft picks from 2006-2017.

I attempted to apply the same models to quarterbacks, as the results could be skewed by possibilities such as that running backs are, for the most part, interchangeable (Hermsmeyer). Furthermore, teams may primarily tank for a quarterback. With the same type of models, all models had a p-value of over 0.3, showing no significant correlation between predictions of quarterback WAR relative to draft pick. It is to be noted, however, that the sample size for quarterbacks drafted in the first round from 2006-2017 is 32.

Discussion

First, I will consider a scenario where a team is considering whether or not to tank and is not planning on tanking for a quarterback specifically. Next, the team is not in playoff contention and is mediocre (~8 wins per season). Here, the data suggests that, at most, for each additional loss the team undertakes as a result of tanking, the team will gain approximately 0.037 wins for each year in the next five years as a result of the player's added skill. This adds up to 0.18 wins combined over the next five years. This is using an AV model to determine WAR; using the method determined by Yurko, Ventura, & Horwitz for WAR for skill players, there is no statistically significant difference in WAR.

The below table shows the mean difference in WAR from pick-to-pick for all players in terms of the AV model.

Table 3: Draft Pick to WAR (AV Model) Pick-to-Pick

	Mean WAR Difference from Pick to Pick
Pick 2 to 1	0.021512
Pick 3 to 2	0.020312
Pick 4 to 3	0.019200
Pick 5 to 4	0.018169
Pick 6 to 5	0.017212
Pick 7 to 6	0.016323
Pick 8 to 7	0.015497
Pick 9 to 8	0.014728
Pick 10 to 9	0.014012
Pick 11 to 10	0.013345
Pick 12 to 11	0.012722
Pick 13 to 12	0.012141
Pick 14 to 13	0.011598
Pick 15 to 14	0.011091
Pick 16 to 15	0.010616
Pick 17 to 16	0.010171
Pick 18 to 17	0.009754
Pick 19 to 18	0.009363
Pick 20 to 19	0.008996
Pick 21 to 20	0.008651
Pick 22 to 21	0.008327
Pick 23 to 22	0.008022
Pick 24 to 23	0.007735
Pick 25 to 24	0.007465
Pick 26 to 25	0.007210
Pick 27 to 26	0.006970
Pick 28 to 27	0.006743
Pick 29 to 28	0.006529
Pick 30 to 29	0.006326
Pick 31 to 30	0.006135
Pick 32 to 31	0.005954

Here, it is depicted that each pick, even toward the first few top picks, only generates a marginal increase in terms of WAR each year, with a maximum of 0.02 from the second to the first pick.

Next, I will consider a scenario where a team is considering whether or not to tank, but if they do tank, they will want to tank for a quarterback in particular. Again, the team is likely not going to be in the playoffs. In this scenario, the data suggests that for each additional loss the team takes, at most, they will gain approximately 0.07 wins each year for the next five years as a result of obtaining a better selection. This adds up to roughly 0.37 wins in the next five years combined. Again, this uses the AV model to predict WAR; previous WAR estimates show no statistically significant difference. Below is a table that shows the WAR added each year for each pick for quarterbacks (n = 112):

Table 4: Draft Pick to WAR (AV Model) Pick-to-Pick for QBs

	Mean WAR Difference from Pick to Pick for QBs
Pick 2 to 1	0.066522
Pick 3 to 2	0.056573
Pick 4 to 3	0.048462
Pick 5 to 4	0.041845
Pick 6 to 5	0.036439
Pick 7 to 6	0.032018
Pick 8 to 7	0.028396
Pick 9 to 8	0.025424
Pick 10 to 9	0.022981
Pick 11 to 10	0.020968
Pick 12 to 11	0.019305
Pick 13 to 12	0.017927
Pick 14 to 13	0.016782
Pick 15 to 14	0.015826
Pick 16 to 15	0.015026
Pick 17 to 16	0.014352
Pick 18 to 17	0.013783
Pick 19 to 18	0.013299
Pick 20 to 19	0.012885
Pick 21 to 20	0.012529
Pick 22 to 21	0.012221
Pick 23 to 22	0.011952
Pick 24 to 23	0.011717
Pick 25 to 24	0.011509
Pick 26 to 25	0.011325
Pick 27 to 26	0.011159
Pick 28 to 27	0.011011
Pick 29 to 28	0.010876
Pick 30 to 29	0.010753
Pick 31 to 30	0.010641
Pick 32 to 31	0.010538

This table shows that the difference in WAR between picks for quarterbacks and for all positions is around an additional 0.01 WAR per pick. One potential explanation for this discrepancy is the small sample size; there were only 112 quarterbacks in the sample, but 571 for all positions, so outliers could account for this.

One potential reason why the approximate value model for WAR differs from that of previous research is that it largely takes into account surface-level statistics, such as passing yards. However, this does not account for the full picture; for example, take Blake Bortles's 2015 season. He recorded an AV of 14, which translates to a WAR of approximately 1.37 in the AV to WAR model. He had over 4,400 passing yards and 35 touchdowns. However, the Jaguars ended up going 5-11 that year. Furthermore, according to PFF, Bortles had 25 "interception-worthy" plays (fifth-highest in the NFL that year), but only 11 turned into interceptions (Davenport). In 2018, only a few years later, Blake Bortles was benched for Chad Henne. The WAR statistic as determined by Yurko, Ventura, & Horwitz accounts for additional items such as pass location and air yards not accounted for by the AV statistic, enabling further evaluation than basic statistics.

One additional reason is that higher draft picks are generally played more. Due to confirmation bias, players that are drafted higher start more games, regardless of actual skill (Riddle). As the number of games played adds to most players' approximate value, this would help explain some of the correlation between pick and WAR determined by AV. Furthermore, more playing time can lead to an increase in basic statistics such as passing yards because those players are simply allowed to play more, leading to an increase in AV.

Therefore, this data suggests that, at best, the effects of tanking are marginal and only add to less than a win per season at the maximum level of tanking (pick 32 to pick 1). This conclusion is supported by previous research. In research predicting the success of quarterbacks in the NFL draft, it is stated that "overall, draft pick is not a significant predictor of NFL performance" (Berri & Simmons).

In “The Loser's Curse: Decision Making and Market Efficiency in the National Football League Draft” (Massey & Thaler), it is discussed that surplus value increases as the pick number increases throughout the first round. What this means is when the compensation given to a player (which decreases as the pick number increases) is subtracted from the performance value generated by a player (performance - compensation), this value increases throughout the first round, so, for example, the 32nd pick has a higher surplus value than the 1st pick. This supports the hypothesis that tanking would not significantly help NFL teams as the surplus value associated with a draft pick would decrease as a team obtains a higher draft selection. Therefore, as a lower draft position requires less compensation, more of a team’s salary cap can be spent on other players in places such as free agency, and teams can potentially gain more value than simply from a higher draft selection. As my study does not take the cap space dedicated to higher draft picks into account, this only further supports the conclusion that, even if WAR may be marginally higher for higher draft picks, this could be partially negated by the increase in cap cost.

The most practiced scenario of performing badly in the NFL in recent memory is shown by the Cleveland Browns. Between 2010-2019, the Browns were in the bottom half of the league. Under Sashi Brown, they stockpiled a large amount of high-value draft picks. In theory, these picks should have enabled them to succeed through better players. However, even in their best season in recent memory, after the accumulation of so many draft picks, they were 18th in total team DVOA in the regular season (Football Outsiders) and barely made the playoffs.

Limitations and Future Research

One large limitation of this study is the lack of publicly accessible WAR data for each position. Although nflWAR provides a detailed analysis for skill position players, this can not calculate WAR for non-skill position players. Moreover, as discussed previously, AV is not a very detailed measure of predicting success. Future studies could potentially use measures such as PFF's WAR measurement to predict success from draft picks. Due to the NFL relying so heavily on a combined team effort on each play, it is difficult to accurately assess the WAR of one specific player when other players on the same team or coaches could be heavily influencing how well that player performs.

Another limitation was the lack of subjects. The sample size of 572 for draft picks between 2000-2017 is not particularly large, and the sample sizes of 112 for skill position players and 32 for quarterbacks from 2006-2017 are even smaller. With more data in the future, different conclusions may be able to be reached regarding the impact of higher draft selections.

Furthermore, the small sample size of skill position players from 2006-2017 enables outliers to heavily influence the model. It does not seem likely, given the amount of money, time, and effort that NFL teams spend on scouting, that there is no difference in the player value between the 1st and 32nd overall pick. With more data, a stronger connection between draft pick and the WAR model developed by Yurko, Ventura, & Horowitz could be established.

When attempting to calculate team revenue, it seems illogical to assume that winning does absolutely nothing to affect the value of a team. For example, as a team makes the playoffs, they are able to play more games in their stadium, leading to a significant increase in ticket revenue. Therefore, future studies that can standardize for other determinants of team value growth, such as new media deals and the sharing of gate receipts, may be able to determine a correlation between winning and value for NFL teams.

Another factor that could impact a team's revenue is the number of star players. If a highly-hyped player, such as Trevor Lawrence, is drafted, this could potentially be correlated to an increase in revenue due to an increase in jersey sales. This could potentially affect team value, helping to increase the value added of a higher draft selection.

Other factors to consider while tanking are a decrease in fans due to a team not doing well as well as potential free-agent signings. Free agents may not want to sign with a team that was, for example, the worst team in the league last year, so this may affect the results of winning in the future.

Conclusion

This study determines the wins added for a team that decides to tank to obtain a higher draft selection. Using an AV model to predict WAR, tanking from the 32nd to the 1st selection adds less than 0.75 wins per year on average for five years when tanking for a quarterback, and tanking from the 16th to the 1st selection only adds less than 0.5 wins a year. For all positions, tanking from the 32nd to the 1st pick adds less than 0.4 wins per year on average for the first five years, and going from the 16th to the 1st adds approximately 0.23 wins per year using the same WAR model. However, other measures of WAR indicate that there may not be any correlation between a higher draft pick and WAR.

Furthermore, I conclude that wins for a team do not influence their value in any statistically significant way. Therefore, tanking in the NFL to increase a team's value in the future cannot be supported by any data in this study.

Teams in the NFL have the ultimate goal of winning a championship. However, in order to get there, there is no data to support the conclusion that significant sacrifices need to be made in terms of winning in the present to achieve that goal in the future.

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