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Quantifying NFL Players' Value With the Help of Vegas Point Spreads Values

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Abstract
This study develops a new method for converting performance statistics into marginal product by using Las Vegas sportsbooks' individual point spread values (PSVs) for National Football League players. This sarticle employs a Tobit model due to the prevalence of player PSVs that are 0. We find that quarterbacks dominate the player's values. Passing yards per game, passing touchdowns, and rushing touchdowns are the only findings that are consistently significantly related to PSVs.

Keywords
point spread values, NFL, marginal product of labor, Vegas, quarterback

JEL Codes: H3, L83, and Z20

Introduction

Sports researchers have used player performance statistics to estimate marginal product in most professional sports leagues and some college sports (Brown, 1993; Hoffer & Friedel, 2014; Humphreys & Pyun, 2017; Lucifora & Simons,

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2003; Macdonald & Reynolds, 1994; Richardson, 2000; Scully, 1974). The literature on professional baseball, basketball, and soccer are particularly voluminous. Marginal production in the National Football League (NFL) remains largely unstudied.

The NFL presents a challenge for any researcher wishing to convert performance statistics to production estimates. While recent research offers some promise—Berri, Humphreys, and Simmons (2013) use performance and body description to estimate offensive lineman value, and Keefer (2013) uses performance to estimate linebacker value—NFL performance remains difficult to quantify. Where statistics are representative of performance, it is difficult to separate the production of players (Berri & Simmons, 2009) because complementarity between players affects an individual player's productivity (Idson & Kahane, 2000).

For the statistics that are well captured, team style of play can skew results. A ball-control offense that relies heavily on running the football, and thus keeping the clock running between plays, will likely have fewer overall plays and will expect different outcomes from each pass and run play than would a team who relies more heavily on the passing game.

Further, the value of individual players, particularly star players, is difficult to identify because the NFL fits the definition of a weak-link sport more like soccer than a strong-link sport such as basketball (Gladwell, 2016).[1] In football, a player's true quality and value are easily masked by a weak link elsewhere on a team (e.g., dropped passes, missed blocks, or blown coverages).[2]

Finally, Leeds and Kowalewski (2001) also note that unlike some sports, comparing the performance of NFL players in different positions is difficult because there is no single statistic that relatively captures performance, unlike in baseball where batting average is a good comparable across all nonpitching position players. Las Vegas point spread values (PSVs) provide that common measure to compare value across positions.

In this study, we seek to avert these major issues by using new data on NFL player PSVs as a starting point for converting statistical performance to marginal production. We contacted Las Vegas casino sportsbooks and used ESPN reports to obtain data on individual player PSVs—the number of points the sportsbook would move the betting line in the event a player could not participate in a game.

Oddsmakers set aggregate point spreads with the intention of maximizing profit. For point spreads, this means setting a line that encourages relatively even money wagered on both teams. That is, a point spread of 8 points does not mean oddsmakers believe a team is 8 points better than the other team, just that the 8-point line will spread bets evenly between the two teams.

The presence of a point spread provides an incentive for players and gamblers to manipulate outcomes. One such manipulation is point shaving, the practice of actively trying to prevent a team from covering a point spread. Point shaving is attractive because unlike purposely attempting to lose, players engaging in point shaving still win and receive a payoff, most likely financial. This gives the player a double benefit. Since players typically only care if they win, not whether their team covers the spread, gamblers can exploit this difference. Since college athletes are not paid, even small financial payoffs yield a large marginal utility. Wolfers (2006) suggest that point shaving is widespread at least in National Collegiate Athletic Association basketball.

However, Bernhardt and Heston (2010) claim that Wolfers's (2006) results are misinterpreted.

> a widely reported interpretation of the patterns in winning margins in college basketball can lead a researcher to conclude erroneously that there is an epidemic of gambling-related corruption. We uncover decisive evidence that this conclusion is misplaced and that the patterns in winning margins are driven by factors intrinsic to the game of basketball itself. (p. 16)

Further, Borghesi (2008) argues point shaving in college basketball is not widespread because the results from the NBA and NFL mimic those of college basketball. Since professional athletes would receive minimal utility from point shaving because of the high cost if caught, the outcomes of professional and collegiate sports should differ. However, they do not.

Even if point shaving is widespread, this should not be problematic for using PSVs as a proxy for marginal product. Oddsmakers do not make a profit from point shaving; the profits from point shaving accrue to the players and gamblers involved in the scheme. Therefore, the lines oddsmakers have no financial interest to bias aggregate or point spreads for individual players.

Instead of point shaving, Borghesi argues that oddsmakers engage in line shading, the practice of inflating the line of strong favorites. Line shading fits the practice of setting lines to maximize profit because bettors tend to heavily favor strong favorites (Woodland & Woodland, 1994), and oddsmakers exploit this bias when setting the initial point spread (Levitt, 2004). If oddsmakers engage in line shaving for aggregate point spreads, it is possible they would do so for individual player PSVs as well.

Therefore, the presence of line shaving would seem problematic for PSVs being a fair representation of a player's marginal product. However, even with line shaving, PSVs still represent a view of the value of a player, even if the overall objective of an oddsmaker is to make profit rather than set the exact market value of a player.[3] The oddsmaker's point spread must be relatively close to the general perception of the market. If not, the oddsmaker risks losing money. Therefore, even if PSVs are not a true market price or marginal value, they are close. At worst, they may show a small upward bias, particularly for star players (e.g., Tom Brady or LeBron James). However, there is no reason for all the PSVs to show an upward bias since not all the players would be part of a team that is always a heavy favorite. The PSVs show a player's value through the revealed preference of the oddsmaker.

PSVs also partially overcome the problem of complementarity. A player's PSV is the oddsmaker's estimation of the player's worth, holding all else constant, because it measures how the individual moves the betting line. The PSVs do not measure how much one player moves the betting line if something else happens, just how much the line moves if the player misses a game.

We begin our analysis with the marginal value each player provided to us by the Las Vegas sportsbooks. We then use performance statistics to predict those PSVs. Our resulting estimates give us parameters that can be used to estimate a player's marginal product.

Overall, we believe our article contributes a foundation for building a literature on NFL player performance and the NFL labor market that will be comparable to those existing in the other major sports (Hoffer & Pincin, 2018). This article proceeds as follows. The second section describes the data and introduces the empirical specifications. The third section presents the empirical results and provides interpretation. The fourth section offers additional discussion, and the final section provides concluding remarks.

Data and Estimation

Data

We compile NFL data on Vegas PSV for the years 2013 and 2016. We gather the 2013 data from R. J. Bell of Pregame.com, a sports betting media company, and contributor to the now defunct Grantland, a sports blog of ESPN. Mr. Bell compiled what he calls the "Vegas consensus" on the injury value for each player (i.e., how much the point spread would change if the player did not play).[4] We obtained the 2016 NFL PSVs from David Solar, an oddsmaker at Sports Insights. Mr. Solar combined PSVs from oddsmakers at Bookmaker.eu, CG Technology, Westgate Superbook, and William Hill. Mr. Solar divides the players into six tiers, splitting the PSVs of each player within a tier. For example, the players in Tier 1 have PSVs of 6–7 points. In keeping with previous data, we use the average PSV within the tier.[5]

PSVs are expressed as a positive number. For example, Tom Brady, a quarterback for the New England Patriots, had a 2016-2017 PSV of 6.5. If Tom Brady missed a game, the PSV would move 6.5 points in favor of the Patriot's opponent. For example, if the New England Patriots were a 7-point favorite to beat the Atlanta Falcons with Tom Brady in the lineup, the Patriots would only be a half-point favorite if Brady was not expected to play. The lowest PSV for a player is 0, meaning the player's absence from the game has no impact on the point spread.

It is important to note that individual PSVs are not fixed and can change throughout the season according to how well the player is playing, how well the player's team is playing, the quality of the player's opponent, among other factors. For our analysis, we use the PSVs that were computed before the relevant seasons started. For example, Mr. Solar provided the PSVs he calculated prior to the start of the 2016

Table 1. Summary Statistics.

Year	Variable	Mean	Standard Deviation	Minimum	Maximum	Observations
2013	Point spread value (NFL)	0.25	0.99	0	7	387
2012	Passing yards per game	23.46	69.60	0	323.56	387
2012	Pass touchdowns per game	0.15	0.45	0	2.69	387
2012	Rushing yards per game	10.43	21.04	−0.26	131.06	387
2012	Rushing touchdowns per game	0.07	0.15	0	0.94	387
2012	Receiving yards per game	20.51	23.17	−0.94	122.75	387
2012	Receiving touchdowns per game	0.12	0.18	0	1	387
2012	Receptions per game	1.77	1.76	0	7.63	387
2012	Interceptions per game	0.09	0.26	0	1.33	387
2012	Fumbles per game	0.06	0.11	0	0.7	387
2016	Point spread value (NFL)	0.29	1.12	0	6.5	411
2015	Passing yards per game	24.01	72.92	0	328.17	411
2015	Pass touchdowns per game	0.16	0.49	0	2.5	411
2015	Rushing yards per game	9.91	19.00	−2	92.81	411
2015	Rushing touchdowns per game	0.06	0.14	0	0.8	411
2015	Receiving yards per game	1.84	1.83	0	8.5	411
2015	Receiving touchdowns per game	21.18	23.51	−2	116.94	411
2015	Receptions per game	0.13	0.19	0	1	411
2015	Interceptions per game	0.08	0.27	0	2	411
2015	Fumbles per game	0.06	0.10	0	0.6	411

Source. www.NFL.com, http://grantland.com/the-triangle/if-he-goes-down-we-go-down-nfl-injury-value-in-vegas/, and https://www.sportsinsights.com/blog/nfl-player-point-spread-values/ for NFL data.

NFL season. These values are best interpreted as the expected impact each player will have on the point spread based on the previous year's performance and expected production. While not ideal, these were the only PSV data we were able to obtain and should provide a rough estimate of a player's overall PSV.

We predict each player's PSV using performance statistics from the previous season in our empirical analysis. We use per game averages of passing yards, passing touchdowns, interceptions thrown, receiving yards, receiving touchdowns, rushing yards, rushing touchdowns, and fumbles from the 2012 (predicting 2013 PSVs) and 2015 (predicting 2016 PSVs) seasons. We collected performance statistics from the NFL official website. Summary statistics for all data are presented in Table 1.[6]

Our data include only players who recorded at least one statistic in one of the independent variables (e.g., at least one-yard rushing or one reception).[7] We also eliminate players who did not record a statistic in consecutive years in the data. For example, if a player played in 2015, they must play in 2016 to stay in the data set since the article is using 2015 data to explain 2016 preseason individual point values. Therefore, there may be a player who played in 2015, then retired or was injured the following season and thus does not have a 2016 PSV, even though they have statistics for the 2015 season. Peyton Manning, the quarterback for the Denver Broncos, for example, played in 2015 and then retired for the 2016 season. Had he played the next year, it is likely he would have had a positive individual PSV. Removing these players helps reduce the likelihood of biasing the estimates and did not change the estimation results in any significant manner.

We consider only offensive skill players: running backs (excluding fullbacks), wide receivers, tight ends, and quarterbacks. We limit our sample to skill players only because only eight defensive players, zero offensive lineman, and zero special team players had a nonzero PSV.[8] This follows Leeds and Kowalewski (2001), who only consider skill positions in their analysis of how the imposition of the salary cap and free agency affected the financial return to increased performance. The authors use skill players only because skill players handle the football more and there is a direct way to measure their personal performance with common performance statistics (e.g., touchdowns) and because other positions lack easily interpretable performance statistics. We drop the rare nonskill player who had a positive statistic, such as the occasional punter who threw a pass or offensive tackle who caught a batted pass.

Model and Estimation

We begin by using performance statistics to explain the PSVs of the NFL and NBA players. Since PSVs are bounded by 0, PSVs are a count variable, and the number of zero PSV observations is considerable, we rely heavily on the Tobit model (Tobin, 1958). In robustness checks, we perform similar estimations using Cragg's (1971) double hurdle model and a zero-inflated Poisson (ZIP) model. The Cragg and ZIP models provided remarkably similar results to the Tobit model, so we do not include those results in the article, but the results are available upon request.

The Tobit model provides two separate estimates for (i) the likelihood of $y > 0$ and (ii) the marginal effect, given $y > 0$. The Tobit model can be expressed as,

$$y = \left\{ \begin{array}{l} y^* \text{ if } y^* > 0 \\ 0 \text{ if } y^* \leq 0 \end{array} \right\},$$

where $y^* = \beta X + \mu,\ \mu : (0, \sigma^2)$.

PSV is the dependent variable in each regression. In our regressions, our explanatory variables include passing yards, passing touchdowns, rushing yards, rushing touchdowns, quantity of receptions, receiving yards, receiving touchdowns, interceptions, fumbles, and a constant. All performance statistics are in per game averages. We use a robust standard error term.

Table 2. Tobit Results 2013 National Football League Season.

Variable	Tobit Model	Marginal Effects at Means for Truncated Sample	Marginal Effects for the Truncated Sample
Passing yards per game	0.03 (0.01)***	0.00 (0.00)***	0.00 (0.00)***
Passing touchdowns per game	3.14 (1.21)***	0.25 (0.11)**	0.41 (0.16)**
Rushing yards per game	0.07 (0.02)***	0.01 (0.00)***	0.01 (0.00)***
Rushing touchdowns per game	1.59 (1.94)	0.13 (0.16)	0.21 (0.25)
Receptions per game	0.62 (0.33)*	0.05 (0.03)*	0.08 (0.04)*
Receiving yards per game	0.03 (0.03)	0.00 (0.00)	0.00 (0.00)
Receiving touchdowns per game	1.07 (1.63)	0.08 (0.12)	0.14 (0.21)
Interceptions per game	−2.81 (1.76)	−0.22 (0.15)	−0.36 (0.24)
Fumbles per game	−1.25 (1.56)	−0.10 (0.23)	−0.16 (0.38)
Number of observations	387		
F statistic	23.30		
Psuedo R^2	0.47		

Note. The dependent variable is point spread value for the 2013 National Football League season. The independent variables are from the 2012 season. The set of regressors also included a constant, which was excluded for reasons of space. Robust standard errors are in parentheses.
***1%, **5%, and *10% significance level.

Results

Table 2 provides the results of the Tobit model for the 2013 NFL PSVs as well as the conditional marginal effects (if the PSV > 0) at the means and the average for the truncated sample.[9] The results show that per game passing yards, passing touchdowns, and rushing yards all increase the likelihood of a player having a positive PSV. The positive signs for each of the variables are also in the expected direction as an increase in each of these variables is a benefit for the players, as opposed to the number of interceptions or fumbles per game.

The sign and statistical significance should not be surprising, as quarterbacks are generally considered to be the most valuable starters in the NFL. Quarterbacks are by far the highest paid players, and quarterbacks have been draft number one overall in 14 of the past 20 NFL drafts.

The signs for interceptions and fumbles per game are negative, as expected, but the coefficients were not statistically different from 0. This result may be driven by the fact that PSVs are truncated at 0 or that players who accrue higher levels of fumbles and interception have short careers and see little time on the playing field.

The middle column of Table 2 presents the marginal effects, given PSV > 0. For the passing statistics, 100 additional passing yards per game increases the PSV for a player by 0.3 and 0.4 points, depending whether we evaluate the marginal effect at the sample mean or average the marginal effect across all players.

We also discuss the marginal effects quantified by a change in 1 *SD* of the independent variable. If a player increases the number of passing yards per game by one standard deviation (131.8 yards), a player's PSV increases between 0.33 and 0.54 points.[10] An additional passing touchdown per game increases the PSV for a player between 0.25 and 0.41 points. In this case, a *marginal effect* of one additional passing touchdown per game is not so marginal, considering this results in 16 additional touchdown passes per season, an incredible increase, especially considering the NFL record for touchdowns in one season is 55. A one standard deviation increase in the number of passing touchdowns per game increases a player's PSV between 0.22 and 0.37 points per game.

For the rushing statistics, 100 additional rushing yards per game increased the PSV for a player between 0.5 and 0.9 points. If a player increases the number of rushing yards by one standard deviation, their PSV increases between 0.21 and 0.35 points. An increase in the number of rushing touchdowns per game is the expected sign but not statistically significant. One possible explanation for this is the existence of specialized, short-distance running backs, running backs who enter the game when a team is close to the goal line because they specialize in short-yardage situations. These backs earn limited carries and rushing yards per game, but they score a disproportionate number of touchdowns. Those touchdowns reduce the number of touchdowns a team's primary back scores, making it more difficult to identify value based solely on yards or touchdowns.

For the receiving statistics, only receptions per game are statistically significant, though only at the 10% level, though it is the expected sign. This is in line with Leeds and Kowalewski (2001) who find that the impact of performance on compensation among skill players in the NFL was lowest for wide receivers and tight ends. An additional reception per game increases the PSV for a player between 0.05 and 0.09 points. A one standard deviation increase in the number of receptions per game increases a player's PSV between 0.11 and 0.21 points.

Table 3 provides the Tobit results, the marginal effects at the means, and the average marginal effects for truncated sample for 2016 PSVs. The results are similar to the 2013 PSVs as per game passing yards, passing touchdowns, and rushing touchdowns increase the likelihood of a player have a positive PSV. For this year, per game rushing yards is the expected sign but statistically insignificant while per game receiving yards is positive and statistically significant. Per game interceptions and fumbles are the expected sign but statistically insignificant.

For the passing statistics, 100 additional passing yards per game increases the PSV value for a player between 0.2 and 0.3 points. If a player increases the number of passing yards per game by one standard deviation, their PSV increases between 0.23 and 0.32 points. An additional passing touchdown per game increases the PSV for a player between 0.22 and 0.31 points. A one standard deviation increase in the number of passing touchdowns per game increases a player's PSV between 0.18 and 0.24 points per game.

Table 3. Tobit Results 2016 National Football League Season.

Variable	Tobit Model	Marginal Effects at Means for Truncated Sample	Marginal Effects for the Truncated Sample
Passing yards per game	0.02 (0.01)**	0.00 (0.00)**	0.00 (0.00)**
Passing touchdowns per game	1.92 (0.86)**	0.22 (0.11)**	0.31 (0.14)**
Rushing yards per game	0.01 (0.017)	0.00 (0.00)	0.00 (0.00)
Rushing touchdowns per game	2.95 (1.42)**	0.34 (0.16)**	0.48 (0.23)**
Receptions per game	−0.56 (0.33)*	−0.07 (0.04)*	−0.09 (0.05)*
Receiving yards per game	0.06 (0.02)***	0.01 (0.00)***	0.21 (0.19)***
Receiving touchdowns per game	1.29 (1.18)	0.15 (0.14)	0.21 (0.19)
Interceptions per game	−0.13 (1.35)	−0.02 (0.16)	−0.02 (0.22)
Fumbles per game	−1.02 (2.23)	−0.12 (0.26)	−0.17 (0.36)
Number of observations	411		
F statistic	25.68		
Psuedo R^2	0.51		

Note. The dependent variable is point spread value for the 2016 National Football League season. The independent variables are from the 2015 season. The set of regressors also included a constant, which was excluded for reasons of space. Robust standard errors are in parentheses.
***1%, **5%, and *10% significance level.

For the rushing statistics, per game rushing touchdowns and not rushing yards is statistically significant, casting doubt on the specialized back effect hypothesis for the earlier results. However, it is plausible that as the NFL continues its progression as a passing league, touchdowns are becoming more valuable.[11] An additional rushing touchdown per game increases the PSV for a player between 0.34 and 0.48. A one standard deviation increase in touchdowns per game increases a player's PSV between 0.06 and 0.08 points. The lower PSVs for the one standard deviation make sense for the same reasons the PSV numbers for passing touchdowns are lower for a one standard deviation change.

For the receiving statistics, per game receiving yards is statistically significant at the 1% level. One hundred additional receiving yards per game increases the PSV for a player between 0.7 and 0.9 points. A one standard deviation increase in per game receiving yards increases a player's PSV between 0.2 and 0.28 points.

Discussion

As a comparison of how well the point estimates from our Tobit model predict the marginal production of NFL players, Table 4 describes the raw-data PSVs, our predicted PSVs, and the difference between the two values for the top 35 NFL players in 2013 and 2016 ranked according to our predicted PSVs. This section provides a few observations regarding the results.

First, quarterbacks dominate the list. In 2013, only nine non-quarterbacks are among the top 35 predicted PSVs while no non-quarterback makes the list in 2016. This makes intuitive sense as quarterbacks handle the football on almost every offensive play and the league has trended toward more passing-reliant offenses.

Second, of the players who are ranked in the top 35 in both years, our performance statistic–based estimations overrate the value of Alex Smith and Ryan Fitzpatrick, compared to the Vegas consensus values. Our estimates, comparatively, underrate the value of Andrew Luck, Andy Dalton, Ben Roethlisberger, Eli Manning, Joe Flacco, Matthew Stafford, Matt Ryan, Nick Foles, Philip Rivers, Russell Wilson, Tom Brady, and Tony Romo.

To interpret these findings, let us first note that our pseudo R^2 values range between 0.4 and 0.6, so we expect a good deal of variation between our predicted PSVs and the Vegas PSVs. It is possible that omitted performance statistics could improve our estimation (i.e., drops or style of play), but we believe the greater driver of the difference in estimates are player qualities that are difficult to capture statistically.

Qualities such as leadership and at-the-line calls are exceptionally difficult to quantify. We know of no-known statistic to quantify audible (play changes or play calls, often made by quarterbacks at the line of scrimmage). Aaron Rodgers is perhaps the best of all time at obtaining and capitalizing on offensive "free plays." An offensive free play occurs when the defense commits an infraction at the snap of the ball—usually offside or too many men on the field—and the play can continue. At the conclusion of the play, the offense can decide to accept the play's outcome or to accept the penalty against the defense, gaining yardage and the ability to replay the down. If a quarterback recognizes the free play opportunity, this allows for a risk-free gamble. A long pass that is completed for a touchdown and a long pass that is intercepted simply results in a gain of yardage and a replay of the down. Statistically, the beneficial outcome manifests in statistical performance; the negative outcome manifests as penalty yardage and no play. These unquantified qualities may be the reason our model suggest Aaron Rodgers was statistically worth 3 less points in 2016 than the Vegas consensus.

Our model identified some outliers before the Vegas consensus. The predicted PSV for Tony Romo in 2016 suggested he was well overrated entering the year, even before he was injured and replaced. The predicted PSV for Eli Manning in 2013 suggested he was overrated by over 3 points, a year in which he threw nine more interceptions than touchdowns. Finally, the predicted PSV for Colin Kapernick was negative for 2016. It is plausible that the reason he was not on an NFL roster in 2017 was more for his play than his politics, at least for some teams.

We can also convert our estimates—changes in PSV—to changes in the likelihood of winning a game (Δw) and expected Δw for a player over a 16-game season. Several studies have used point spreads to predict football game outcomes (Pankoff,

Table 4. NFL Tobit Point Estimates.

2013				2016			
Player	PSV	Predicted PSV	Difference	Player	PSV	Predicted PSV	Difference
Aaron Rodgers	6	7.07	1.07	Blake Bortles	4	5.83	1.83
Drew Brees	6	6.45	0.45	Cam Newton	6.5	5.74	−0.76
Tom Brady	6.5	6.26	−0.24	Tom Brady	6.5	5.40	−1.10
Peyton Manning	7	5.55	−1.45	Drew Brees	5.5	5.18	−0.32
Matt Ryan	5.5	4.77	−0.73	Carson Palmer	5.5	4.57	−0.93
Robert Griffin	3.5	4.71	1.21	Andrew Luck	6.5	4.12	−2.38
Ben Roethlisberger	5	3.87	−1.13	Russell Wilson	5.5	4.11	−1.39
Cam Newton	0	3.86	3.86	Geno Smith	0.5	4.11	3.61
Tony Romo	3	2.96	−0.04	Ben Roethlisberger	6.5	4.07	−2.43
Adrian Peterson	2.5	2.89	0.39	Eli Manning	5.5	4.00	−1.50
Russell Wilson	3	2.82	−0.18	Matthew Stafford	4	3.87	−0.13
Shaun Hill	0	2.61	2.61	Andy Dalton	4	3.86	−0.14
Matthew Stafford	3.5	2.51	−0.99	Kirk Cousins	4	3.86	−0.14
Andrew Luck	3	2.50	−0.50	Philip Rivers	4	3.79	−0.21
Josh Freeman	0	1.63	1.63	Ryan Fitzpatrick	0.5	3.61	3.11
Andy Dalton	4	1.63	−2.37	Aaron Rodgers	6.5	3.59	−2.91
Carson Palmer	0	1.55	1.55	Derek Carr	3	3.35	0.35
Eli Manning	4.5	1.30	−3.20	Jameis Winston	3	3.31	0.31
Joe Flacco	4	1.25	−2.75	Joe Flacco	5.5	3.30	−2.20
Doug Martin	0.5	1.11	0.61	Marcus Mariota	3	3.19	0.19
Matt Schaub	2.5	1.03	−1.47	Josh McCown	0.5	2.86	2.36
Mike Vick	0	0.98	0.98	Tyrod Taylor	3	2.85	−0.15
Alex Smith	0	0.88	0.88	Ryan Tannehill	3	2.83	−0.17
Sam Bradford	3	0.61	−2.39	Brian Hoyer	0	2.69	2.69
Philip Rivers	4	0.59	−3.41	Matt Schaub	0	2.68	2.68
Ryan Fitzpatrick	0	0.54	0.54	Matt Ryan	4	2.49	−1.51
Arian Foster	1.5	0.44	−1.06	Blaine Gabbert	0.5	2.44	1.94
Ray Rice	0.5	0.06	−0.44	Jay Cutler	2	2.37	0.37
Marshawn Lynch	0.5	−0.17	−0.67	Brock Osweiler	2	2.21	0.21
Jay Cutler	3.5	−0.29	−3.79	Sam Bradford	0.5	2.15	1.65
Calvin Johnson	1.5	−0.34	−1.84	Alex Smith	2	2.10	0.10
LeSean McCoy	0.5	−0.34	−0.84	Tony Romo	5.5	1.33	−4.17
Nick Foles	0	−0.55	−0.55	Colin Kaepernick	0.5	−0.14	−0.64
Alfred Morris	0	−0.57	−0.57	Mark Sanchez	0.5	−0.22	−0.72
Jamaal Charles	1.5	−0.57	−2.07	Nick Foles	0	−0.29	−0.29

Note. PSV = point spread value.

1968; Stern, 1991; Vergin & Scrabin, 1978). Stern (1991) used data on point spreads and game outcomes across five NFL seasons and concluded, “margin of victory for the favorite is approximated by a Gaussian random variable with mean equal to the point spread and standard deviation estimated at 13.86.”

In Table 5, we present the conversion rate of PSV to Δw. A player with a PSV of 1.0 increases the likelihood of his team winning by approximately 2.8%. Over the course of 16 games, the expected increase in wins from a 1.0 PSV player is 0.45. A player with a 6-point PSV increases the likelihood his team wins a game by 16.8%, which translates to 2.7 wins over the course of a season.

Conclusion

In this article, we estimated PSVs for NFL players. To our knowledge, we are the first to provide such estimates for NFL players.

While we believe our PSVs are reasonable estimates of marginal production of NFL players, we identify limitations in our research and avenues for future research. First, we were limited to two cross sections of data for NFL players separated by 3 years. Additional PSV data could allow for a panel analysis. While the cross section allows us to provide predicted PSV’s for each year, the cross section does not let us see the overall marginal production of a player through time. For example, our model suggests Aaron Rodgers was undervalued in 2013 but overvalued in 2016. A longer data set would create more precise and consistent estimates.

Second, the only PSV data available to us were the PSVs developed before the start of the season. This is suboptimal compared to PSV data that are updated as the season progresses. For example, a lingering midseason injury could decrease a player’s production. Oddsmakers would take this injury into account when setting the weekly betting line. Researchers could also update their model with in-season data (e.g., using data of Week 1 to help predict the PSV of Week 2). This would allow the researcher to consider more players throughout the season.

For example, a rookie at the beginning of the season may not have a PSV because of the uncertainty of their performance. However, by midseason, it may be clear that the player is valuable to the team’s success. For example, consider Ezekiel Elliott, the rookie running back for the Dallas Cowboys in 2016. While he was a high draft pick, it was unclear at the start of the season how valuable he would be for the Cowboys, like any rookie. By the end of the season, Elliott lead the NFL in rushing yards and was named to the NFL All-Pro team. His performance surely influenced the betting lines oddsmakers set week to week. Weekly data would provide a more comprehensive picture of the player’s value throughout the season.

Finally, the Vegas PSVs identify only about 35 offensive players per season and fewer than 10 defensive players per season whose PSV is greater than 0. While we found this observation rather stunning in itself—in 2013, of all defensive players in the league, only J. J. Watt (1 point), Darrelle Revis, DeMarcus Ware, Clay

Table 5. Point Spread Values and Expected Wins.

Added Value to Point Spread	Percentage Point Increase of Winning a Game[a]	Expected Increase in Wins for a 16-Game Season
0.5	1.3	0.21
1	2.8	0.45
1.5	4.3	0.69
2	4.5	0.72
2.5	7.1	1.14
3	8.6	1.38
3.5	9.9	1.58
4	11.4	1.82
4.5	12.7	2.03
5	14.1	2.26
5.5	15.4	2.46
6	16.8	2.69
6.5	18.1	2.90
7	19.3	3.09
7.5	20.5	3.28

[a]Percentage point increase of winning a game based on Stern (1991) who finds that margin of victory outcomes are approximated with a Gaussian distribution centered at the point spread, with a standard deviation of 13.86.

Matthews, Louis Delmas, Joe Haden, Von Miller, and Troy Polamalu (0.5 points each) would move the points spread any amount if unable to play—the lack of positive PSVs severely limits the power of the statistical models to explain productivity performance. Indeed, we drop all defensive players from this statistical analysis. Future research may be able to identify more nonzero PSVs, perhaps at the single-game level, that may allow for more precise estimates.

Despite these limitations, we see these estimates as a high-quality first estimate of NFL players' marginal production and a foundation for building a literature on NFL players' performance and the NFL labor market that will be comparable to those existing in the other major sports.

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Notes

1. A sport is a weak-link sport if improving the weakest positions improves performance more than improving the strongest positions at the margin. A sport is a strong-link sport if improving the strongest positions improves performance more than improving the weakest positions at the margin. In basketball, the superstar players have a much greater impact on the game than role players because the superstar player can dominate control of the basketball, making basketball a strong-link sport.
2. A simplified version of the O-Ring production function of Kremer (1993) provides a good explanation of how weak and strong links interact. Suppose a player's expected production function is modeled as $E(y) = (\sum_{i=1}^{n} qi) \times n$, where n is the number of interactions between players (e.g., passes thrown from a quarterback to a receiver) and q is the quality of each task (i.e., the chance of success), with $q = 1$ meaning the task is completed perfectly (e.g., a completed pass). Like Kremer, we assume the probability of mistakes by different players is independent. Suppose an All-Pro quarterback (a strong link) completes 70% of their passes (i.e., $q = 0.7$) and an All-Pro receiver (a strong link) catches 95% of passes thrown to them (i.e., $q = 0.95$). For any given pass ($n = 1$), the expected success of a completion is 66.5%. Now, suppose the All-Pro quarterback is injured and replaced by a backup (a weak link), who only completes 50% of their passes (i.e., $q = 0.5$). Now, for any given pass ($n = 1$), the expected success of a completion is 47.5%. Thus, a wink-link player reduces the value of the strong-link player, even though the remaining strong-link player's ability did not diminish.
3. See Levitt (2004) for a wider discussion on how oddsmakers are different than market makers in financial markets.
4. See the link for additional details: http://grantland.com/the-triangle/if-he-goes-down-we-go-down-nfl-injury-value-in-vegas/
5. See the following link for further information: https://www.sportsinsights.com/blog/nfl-player-point-spread-values/
6. We also perform statistical analyses and summaries using only the truncated data for with PSV > 0. Those summary statistics and statistical analyses are available upon request.
7. For the NFL, this eliminates any player who made the 53-man roster but never made the game day 46-man roster.
8. Making these changes do not change the basic results, which are available upon requests.
9. Marginal effects at the means find the marginal effect an independent variable has on the dependent variable, holding the other independent variables constant at their means. The average marginal effect shows the marginal effect an independent variable has on the dependent variable using more information. See Williams (2012) for additional details.
10. We calculated these numbers, and all future standard deviation changes, by multiplying the relevant marginal effect (i.e., at the sample mean or average marginal effect across all players) by the standard deviations of the truncated sample (PSV > 0).
11. Unfortunately, having PSV data for only 2 years prevents us from making a firmer conclusion on the inconsistent rushing results between the 2 years.

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