

Evaluating the Impact of Special Teams on Winning

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Abstract

1 This paper evaluates the per-play impact of special teams on the winning percentage of NFL
2 teams compared to offense and defense. Employing data from the 1999-2022 NFL seasons in the nflfastR
3 database, we developed a new calculation for Expected Points Added (EPA) to accurately assess the
4 contribution of special teams plays, including punts, kickoffs, and field goals, independent of coaching
5 decisions. This methodology allowed us to create our Special Teams Performance Index (STPI), a
6 composite metric that consolidates the performance of all special teams units on a team. We then used
7 STPI in combination with offensive and defensive ratings from ProFootballReference in a regression
8 model to evaluate the importance of special teams on winning percentage. Finally, since there are fewer
9 plays on special teams than on offense or defense in a game, we adjusted the resulting numbers to find the
10 impact on a per-play basis. We found that an individual play on offense is 3.6 times and that an individual
11 play on defense is 2.6 times more impactful on winning percentage than a play on special teams. Our
12 results can be extrapolated to coaching decisions concerning playing starters on special teams. A special
13 teams play has a significantly lower impact on a game as compared to one on offense or defense, and
14 plays on special teams have a significantly higher per-play injury rate; therefore, starters on offense and
15 defense should generally not be used on special teams.

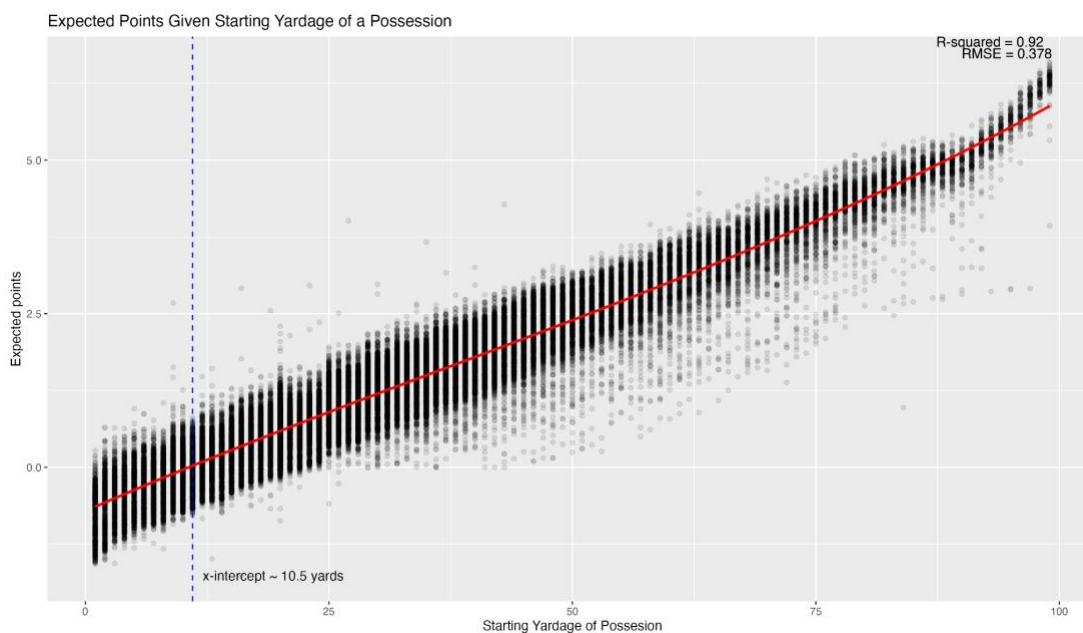
16 Introduction:

17 Special teams plays, including punts, kickoffs, field goals, and extra points, can significantly
18 influence a football game's outcome. While extra points are limited almost exclusively to a make or a
19 miss, all other special teams plays can affect the score of a game through the resulting field position. For
20 example, a missed field goal can set up the opposing team with a field position that makes scoring points
21 easier. Similarly, pinning a team back at their two-yard line after a punt undoubtedly makes it harder for
22 them to score, but just how impactful is this play in the course of a game? George Allen, a Pro Football
23 Hall of Fame coach, once asserted that: "Football is one-third offense, one-third defense, and one-third
24 special teams," but his commentary was not grounded in analytics. Research has been published
25 concerning the importance of punting by the 33rd Team, but, according to this model, the top five punting
26 units all had negative expected points added (EPA). Like many others, this EPA model took into account
27 coaching decisions of whether to punt or go for it when calculating the EPA for a given play. Such
28 decisions, when statistically incorrect (i.e. the coach should have elected to go for it), automatically lower
29 the EPA of a punt, regardless of the outcome of the play. Our research aimed to determine the effect that
30 the entirety of a special teams unit can have on a team's winning percentage relative to its offensive and
31 defensive units on a per-play basis, independent of erroneous coaching decisions.

32 Materials and Methods:

33 An EPA model was used to isolate and measure the performance of special teams units, which
34 measures the actual point value of a given play compared to the expected points derived from historical
35 averages; however, as described earlier, the EPA models that come in datasets like nflfastR, account for
36 incorrect coaching decisions like punting/attempting field goals instead of going for it, rather than directly
37 measuring on-field player performance. Thus, we calculated a new form of EPA by creating an expected
38 points (EP) model to determine the value of a special teams play solely based on the starting field

39 position, eliminating the impact of coaching decisions. This was accomplished by plotting the starting
 40 field position of every drive in the dataset along with each drive's result (in points). Our EP model would
 41 serve as the baseline for calculating EPA. Below is our cubic regression model of EP vs. Starting field
 42 position from the 1999-2022 seasons, which consisted of 79,389 total possessions:



43
 44 Kicking it off with kickoffs. We analyzed kickoffs using data from the 2016-2022 NFL seasons, a
 45 period chosen because of a rule change that moved the touchback from the 20-yard line to the 25-yard
 46 line. To calculate the EPA for kickoffs, we first determined the average resulting field position after a
 47 kickoff, which was the 25.52-yard line. Using a version of our EP model with only data from the 2016-
 48 2022 seasons, we calculated the expected points a team would score from this average field position. We
 49 then calculated the expected points value from the actual starting field position of each kickoff. Taking
 50 the difference of these two values gave us the EPA for each kickoff for the kicking team. The EPA for the
 51 receiving team is simply the negative of this value. We then calculated the average EPA per kickoff for
 52 both kicking and receiving teams for each season and analyzed how these averages correlated to the
 53 teams' winning percentages.

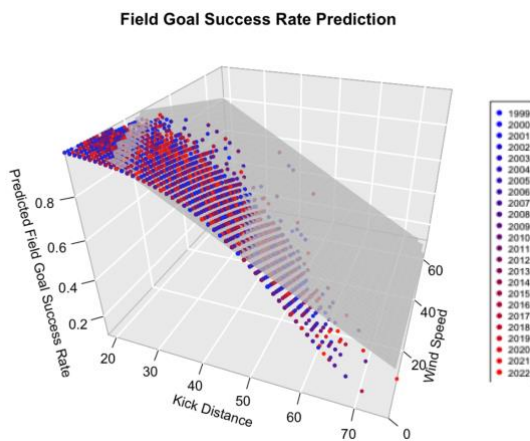
54 To calculate the EPA for each punt, we used the average resulting field position for each yardage
 55 where a punt was kicked from. Due to small sample sizes at some of the yardages, we calculated this by

56 averaging the net positions of punts kicked within two yards of each other. For example, to determine the
 57 average resulting position for a punt from the 3-yard line, we used data from punts kicked from the 1-yard
 58 line to the 5-yard line. We applied our EP model to each average result to estimate expected points for a
 59 punt at every yardage. We then calculated the expected points for each punt's actual resulting field
 60 position. The difference between these two expected points values gave us the EPA for the punting team
 61 for each punt. By taking the negative value of this EPA, we obtained the EPA for the punt return team.
 62 We averaged the EPA of all punts for each team and each season and then analyzed how these averages
 63 correlated with the teams' winning percentages.

64 To calculate the EPA of a field goal attempt, two factors must be evaluated: the expected points
 65 for the field goal and the impact of the field position given to the opponent on a miss. The expected points
 66 for a field goal is the likelihood of success multiplied by three, making the EPA for any successful FG:

$$67 \quad EPA_{Made\ FG} = 3 - (3 * Probability_{field\ goal\ make})$$

68 To calculate the probability of a successful field goal, we created a regression plane, factoring in kick
 69 distance and wind speed for field goal attempts from 1999-2022:



70
 71 On a missed field goal, the value of the field position given to the opposing team is calculated by
 72 comparing the field position's expected points value to the expected point value of the average starting
 73 field position after a kickoff (the result if the field goal had been made). Thus, the EPA for a missed field

74 goal is the negative value of the expected points for the field goal minus the difference between the
 75 expected points of the resulting field position and the average starting position from kickoffs:

$$76 \quad EPA_{Missed\ FG} = -(3 * Probability_{field\ goal\ make}) - (EP_{field\ position} \\ 77 \quad \quad \quad - EP_{average\ field\ position\ from\ kickoffs})$$

78 We did not factor in the expected points of the field position given to a team after a field goal miss if all
 79 possessions in the same half following the missed field goal have a combined likelihood of less than 5%
 80 chance of scoring (as per nflfastR's no_score_prob), such as when there is insufficient time left for the
 81 opposing team to score or when a team chooses to kneel. We then calculated the average EPA per field
 82 goal for each team in every season between 1999-2022 and analyzed how these averages correlated to the
 83 teams' winning percentages.

84 To compare the impact of special teams units as a whole, we created our own Special Teams
 85 Performance Index (STPI). This was created using the sum of the standardized average EPAs for each
 86 special teams unit on every team in every season. Using the standardized Offensive and Defensive Simple
 87 Rating Systems (OSRS and DSRS) from ProFootballReference and a standardized STPI, we ran a
 88 multiple logistic regression model to find the impact of offense, defense, and special teams on winning
 89 percentage. We also ran a regression model without the inclusion of our STPI to compare the difference
 90 in root mean square error (RMSE) and see if there was an improvement in our rating. By using STPI and
 91 thereby including special teams plays that only encompass 15% of all plays in NFL games, we improved
 92 the RMSE as compared to the model with only OSRS and DSRS by 1.9%, from 0.107 to 0.105. Taking
 93 the ratio of the coefficients from the logistic regression model would allow us to compare the impact of
 94 special teams to offensive and defensive units separately as it pertains to winning; however, since special
 95 teams units are on the field less than the offense and defense, we divided our results by the ratio of plays
 96 each unit is involved in (excluding QB kneels and spikes) to find the difference in per-play impact on
 97 winning percentage.

98 **Results and Conclusion:**99 **Results from Multi-Regression Model:**

Coefficients:	Estimate:
z_OSRS	0.55645
z_DSRS	0.40596
z_STPI	0.02877

Number of Occurrences per Play Type:

Play Type:	Number of Occurrences:	Percentage:
Pass	463,377	48.68%
Run	340,589	35.78%
Kickoff	63,860	6.71%
Punt	59,644	6.27%
Field Goal	24,356	2.56%
Total	951,826	

100 The top left table contains the results from our multi-regression model, with each coefficient
 101 representing their impact on winning percentage. From this, we determined that offense and defense were
 102 19.3 times and 14.1 times as impactful over the course of a game as special teams, respectively. To
 103 compare the impact on a per-play basis, we divided the results from the regression by the ratio of plays on
 104 special teams to offense/defense, given by the top right table. We found that one play on offense and
 105 defense is 3.6 times and 2.6 times more impactful on a higher winning percentage than a special teams
 106 play, respectively.

107 Our results can be extrapolated to coaching decisions on deciding if starters should play on
 108 special teams. Special teams has a significantly reduced per-play impact on a game compared to offense
 109 and defense and a significantly higher per-play injury rate; therefore, starters on offense and defense
 110 should generally not be used on special teams.

111 A further extension of this analysis would be to isolate the kickoff or punt unit from the return
 112 unit on each play, using advanced tracking data. This would allow for assessing how much of the
 113 resulting EPA stems from the performance of the kicking teams versus the return team, rather than the
 114 combination of both units on the field. Finally, the new kickoff rules passed by the NFL have the

115 potential to alter how kickoffs are executed and valued. By moving touchbacks up to the 30-yard line, the
116 NFL will encourage more returns on kickoffs, increasing variability in results and the importance of the
117 play to both the return and kicking units. It will be interesting to rerun this analysis next year on the 2024-
118 2025 NFL season data to determine how this change affects the value of kickoff units and special teams
119 as a whole.

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<https://pro-football-reference.com/>