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PREDICTING THE FUTURE OF FREE AGENT RECEIVERS AND TIGHT ENDS IN THE NFL

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Abstract: *While the NFL Draft is an important way to add new talent in the National Football League, free agency is the primary method for teams to acquire veteran players. Veteran players cost teams more money to sign, making it critical for teams to ensure that the free agents they sign are worth their higher salaries. We focus on predicting the future salary, performance, and value of free agents at the wide receiver and tight end positions. These two positions have recently gathered attention as the NFL has transitioned to more passing-oriented offenses. We use player's physical attributes, college performance, and NFL performance to date to create regression and tree models that predict the likelihood that a player is signed, how much they will cost, and how productive the player will be in the future. We find that there are differences between the predictors of salary and the predictors of future performance, which suggests teams are not efficiently evaluating free agents at these positions.*

Keywords: *National Football League, Prediction, Linear Regression, Recursive Partitioning Trees.*

1. INTRODUCTION

In addition to the NFL Draft, free agency is a primary method for adding talent to an NFL team. Mulholland and Jensen (2014) used statistical models to predict the draft order and future success of NFL prospects at the tight end position. However, predicting the signing and future performance of free agents is a distinct problem. Free agents already have experience in the league and so additional information can be incorporated into their predictions. Additionally, unlike drafted players, there is no set wage scale for free agents. Players selected in the NFL Draft have contracts that are pre-determined for the first 4 years of their career based on when they are chosen in the draft. Meanwhile, free agents can negotiate their own salaries with any team they desire. Thus, to effectively model NFL free agency, we must model both future player performance and salary, as teams would like to find players who will have high performance for relatively low cost.

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In American football, the goal is to advance the ball, through a series of plays, to the opposing end of the field to score a touchdown. The ball can be advanced through running plays or passing plays. Running plays usually feature the running back carrying the ball as far as he can before being tackled. Meanwhile, a passing play features the quarterback throwing the ball to one of the skill-position players (usually a wide receiver or tight end).

Pass-catching positions have grown in importance in the NFL in recent years, as many NFL teams now pass on over 60% of their offensive plays. For example, the average salary devoted to the tight end position grew from $974,761 (1.1% of the team's salary cap) in 2005 to $1,960,944 (1.6% of their team's salary cap) by 2013. In 2005 only one tight end free agent signed a contract with an average salary over $1.5 million, while in 2013, ten tight end free agents signed contracts worth that much, including six contracts averaging at least $4 million (3.3% of their team's salary cap).

Wide receivers are often regarded as being worth a substantial portion of a team's salary cap. For example, the Miami Dolphins signed Mike Wallace to a 5-year $60 million deal in 2013. This average salary of $12 million is 9.8% of the $123 million salary cap from 2013. No tight end (whether reaching free agency or not) has ever signed a contract worth over $10 million per year, while several wide receivers take an even larger portion of the salary cap (especially the Calvin Johnson and Larry Fitzgerald contracts that were worth over $16 million per year).

With increasing salaries, it is becoming even more important to maximize the value achieved from signing each player. As a cautionary tale, consider tight end James Casey who was signed in the 2013 offseason by the Philadelphia Eagles to a 3-year contract with an average salary of $4 million. Over the 2013 and 2014 seasons, Casey accumulated only 90 receiving yards and two touchdowns on six catches and was the third tight end on the Eagles depth chart. He was then cut following the 2014 season. It is important for NFL teams to avoid overpaying players for their performance given the constraint of the salary cap. In this paper, we will present models for predicting future performance of free agent tight ends and wide receivers as well as models for predicting future value in terms of performance per unit of cost.

In creating our prediction models, we use only quantitative variables that would be available to teams at the time of their free agent decisions. These predictor variables include each free agent's physical measures, college attended, college performance, and NFL performance (and salary) to date. Dhar (2011) used similar statistical models to analyze wide receiver draft prospects, as did Mulholland and Jensen (2014) to analyze draft decisions for tight ends.

In Section 2, we outline our available data and discuss the statistical methodology used in our analysis. In Section 3, we present predictive models for which free agents will be signed and what those players will be paid, while Section

4 presents predictive models for the subsequent performance and value of those players. Section 5 compares the set of variables predictive of free agent signings (Section 3) to the set of variables predictive of future performance (Section 4). Then, in Section 6, we discuss models we created to predict a different NFL performance measure, approximate value, for comparison to our models from Section 4. We conclude with a discussion in Section 7. However, as an appendix, we also present a case study where our models' predictions for the 2014 wide receiver free agent class are evaluated.

2. DATA AND METHODOLOGY

Our study focuses on all unrestricted free agent tight ends and wide receivers from the 2005 offseason until the 2013 offseason, which were the years available on ESPN's NFL Free Agent Tracker (http://espn.go.com/nfl/freeagency/) at the time. This includes 242 free agent tight ends (of which 156 were signed) and 372 free agent wide receivers (of which 235 were signed). We also obtained data for the 67 free agent wide receivers from the 2014 offseason in order to evaluate our predictions in the appendix.

We allow only predictor variables in our models that are known to teams at the time of their free agent signing decisions. Specifically, teams are aware of each player's physical attributes, college attended, college performance, NFL performance to date, and NFL salary to date. For our outcome variables in Section 4, we also need data for the subsequent NFL performance and salary of these players after their free agency period. All of the data that we gathered for this study are available on public websites.

The physical attributes, college attended, and NFL performance data (both before and after free agency) were obtained from pro-football-reference.com. Physical attributes include age, height, weight, and BMI, which are measured at the NFL Combine before a player enters the league. College attended was used to create indicator variables for conference that each player competed in. For tight ends, we identified whether the player competed in a BCS-level (Bowl Championship Series – i.e. division I-A) conference or not, while for wide receivers, we additionally identified whether a receiver played in the Southeastern Conference (SEC), Big Ten, Pacific 12 (Pac-12), Big 12, or Atlantic Coast Conference (ACC).

The NFL performance data include years played in the NFL, games played, games started, receiving yards, receiving touchdowns, and Pro Football Reference's "approximate value" (AV). We used these variables to create additional measures of receiving production: NFL career score, NFL career score per game, and NFL career score per year. NFL career score is calculated as:

$$\text{NFL Career Score} = \text{Receiving Yards} + 19.3 \times \text{Receiving Touchdowns}$$

The multiplier of 19.3 comes from the analysis of Stuart (2008) which found that 20.3 is the average yardage distance that is equal in value to scoring a receiving touchdown from the one-yard-line, as calculated from the expected point totals for each location on the field. One yard must be subtracted due to the one yard that must be advanced to score a touchdown from the one-yard-line, giving 19.3 as the yardage value equivalent to a receiving touchdown. NFL career score is a measure of aggregate receiving production, while NFL career score per game and per year are measures of average receiving production. Note that each of these measures was calculated separately for the pre-free-agency career versus the post-free-agency career of each player.

Approximate value is a measure that Pro Football Reference uses to estimate a player's production. We use this variable as an alternate NFL performance measure to evaluate the validity of our use of games started and the NFL career score measures.

College performance data were obtained from sports-reference.com/cfb. The data include each player's total receptions, receiving yards, and receiving touchdowns for their college career. We created the additional variables of career college yards per reception and final year percentages of receptions, yards, and touchdowns (i.e. the percentages of each of these three statistics that were accumulated in the player's final college season).

Salary data were obtained from spotrac.com and the USA Today salaries database. We focus on the "cap hit", the portion of the salary cap consumed by each player, as this is the value that is most important to NFL teams. NFL teams must adhere to a strict salary cap, meaning that the sum of all players' cap hits on each team must be below a certain level (i.e. the salary cap). We also assign each player a "cost" as the logarithm of his average cap hit (since salary data tend to behave log-normally).

We also considered using results from the pre-draft NFL combine for each player. However, the available combine data begins in 1999 and since many of the free agents in our sample entered the NFL prior to 1999, there were not sufficient data.

Overall, for predicting tight end-related outcome variables, there are 16 possible predictor variables: an indicator of having attended a BCS college, age, height, weight, BMI, the seven college receiving statistics, and the four NFL performance to date variables. For wide receiver-related outcome variables, we add an additional five possible predictor variables: the college conference indicator variables. Also, for predicting salary, there is the one additional possible predictor of salary to date.

We will employ two different types of statistical models using all of these predictor variables: ordinary least squares linear regression and recursive partitioning trees. We also employ a logistic regression model for the binary outcome of whether or not a free agent will be signed. We implement these models using JMP10 statistical software.

In our linear regression models, we use stepwise variable selection (Hocking, 1976) to identify the subset of predictor variables that maximizes the predictive power of the model, as measured by adjusted R^2. In addition to this variable selection, our regression analysis is helpful for examining the partial effects of individual predictor variables. However, we will be cautious about interpreting our partial effects due to the presence of multicollinearity.

To explore the possibility of non-linear effects and interactions between predictor variables, we also employ recursive partitioning tree models. Recursive partitioning models (Breiman *et.al*., 1984) estimate a decision tree that predicts an outcome value for groups of observations that are partitioned into terminal nodes based on binary splits on a subset of the predictor variables. The particular predictor variables used (and the splitting values) are calculated to maximize the logworth = $-\log_{10}$(*p value of F statistic*), where the *F statistic* measures the ratio of the between-node variance to the within-node variance. A larger logworth indicates a greater difference between the terminal nodes and hence greater predictive power for the model. We prune each decision tree branch if the number of observations in the terminal node falls below 40 or if there are no possible splits that have a logworth greater than 1.3, which indicates that each split is significant at the 5% level ($-\log_{10}(0.05) = 1.3$).

The variables that are used as splitting variables closer to the initial node of the tree tend to have the highest logworth and are, therefore, the most significant. We do note that recursive partitioning has a tendency to select continuous variables over categorical variables (Strobi *et.al.*, 2007), but we have found that in our models some of the dummy variables were selected at a relatively high frequency.

We compare the fit of our regression and tree models using the root mean square error (RMSE) of the predicted values from each model, where RMSE is defined as the square root of the average of the squares of the differences between the predicted and actual values of the outcome variable. Our logistic regressions are evaluated using R^2 values based on Cox and Snell (1989).

3. PREDICTING FREE AGENT SIGNING AND FREE AGENT SALARIES

Whether a team decides to sign a free agent and for how much money are indications of how productive the team believes that free agent will be in the future. Our first set of models predict whether or not each free agent player will be signed and for how much money (in terms of average salary cap hit). These models will allow us to assess which predictors are currently important in NFL teams' evaluation of tight end and wide receiver free agents.

A summary of all of the models presented in this section, as well as those from the following section, can be seen in Tables 1-4. Table 1 and Table 2 show the variables selected for the regression models for tight ends and wide receivers, respectively. In these two tables, a blank implies the variable was not selected for that model, a "+" implies that variable was selected with a positive coefficient, and a "-" implies that variable was selected with a negative coefficient. Additionally, if the "-" or "+" is in gray shading, that indicates that the variable was significant at the 5% level for that given model. Table 3 and Table 4 show summary statistics of the tight end and wide receiver models, respectively.

Tab. 1: Tight End Regression Model Variables. Rows are predictor variables and columns are response variables. "+" means selected by the model with a positive coefficient, " – " means selected by the model with a negative sign, and a blank cell means not selected by the model. Gray shading indicates that the predictor variable was significant at the 5% level for that given model.

Variable	Signed vs. Unsigned (logistic)	LN (salary) PFA	NFL Games Started PFA	NFL Career Score PFA	NFLCS per Game PFA	NFLCS per Year PFA	NFL Games Started per Cost PFA	NFL Career Score per Cost PFA	NFLCS per Games per Cost PFA	NFLCS per Year per Cost PFA
Age in Upcoming Season	–		–	–	–	–	–	–	–	
Height										
Weight	–									
BMI										
BCS	+									
Career College Yards per Reception	+				+	+				
Career College Reception		+			+	+				
Career College Yards		–		–	–	–		–		
Career College Touchdowns		+	–			–	–			
Final Year College Rec Percentage					–					
Final Year College Yards Percentage	+									
Final Year College TDs Percentage	–				+					
NFL Games Started (per cost) to Date	+		+		–	–	+		–	–
NFLCareer Score (per cost) to Date	–	–								
NFLCS per Game (per cost) to Date	–	–			+					
NFLCS per Year (per cost) to Date	+	+		+	+	+		+	+	+
Average Cap Hit to Date										

Tab. 2: Wide Receiver Regression Model Variables. Rows are predictor variables and columns are response variables. "+" means selected by the model with a positive coefficient, "–" means selected by the model with a negative sign, and a blank cell means not selected by the model. Gray shading indicates that the predictor variable was significant at the 5% level for that given model.

Variable	Signed vs. Unsigned (logistic)	LN (salary) PFA	NFL Games Started PFA	NFL Career Score PFA	NFLCS per Game PFA	NFLCS per Year PFA	NFL Games Started per Cost PFA	NFL Career Score per Cost PFA	NFLCS per Games per Cost PFA	NFLCS per Year per Cost PFA
Age in Upcoming Season	–		–	–	–	–	–	–	–	–
Height								–		
Weight					–	–			–	–
BMI		–								
SEC										
Big Ten			+	+	+	+	+	+	+	+
Big 12			–	–	+					
Pa-12			–	–			–	–		
ACC			–	–			–	–		
BCS		–	–	–	–	–	–	–	–	–
Career College Yards per Reception							+			
Career College Reception									+	+
Career College Yards					+	+	+			
Career College Touchdowns		–			–	–			–	
Final Year College Rec Percentage							+			+
Final Year College Yards Percentage										
Final Year College TDs Percentage		–			–	–	–		–	–
NFL Games Started (per cost) to Date	–	–	–			–				
NFLCareer Score (per cost) to Date						+				
NFLCS per Game (per cost) to Date	–	–		+	+		+	+	+	
NFLCS per Year (per cost) to Date	+	+	+			+				+
Average Cap Hit to Date		–								

3.1 FREE AGENT SIGNING

Our fitted logistic regression model for whether or not each free agent tight end was signed by a team has an R^2 value of 0.152 (significant at the 0.01% level). Ten (of 16 possible) predictor variables were selected by the model, seven of which have partial effects that are significant at the 5% level. The selected predictors for tight ends include physical variables (age and weight), college variables (BCS indicator, career yards per reception, final year yards percentage, and final year touchdowns percentage), and NFL performance to date variables (NFL career score to date, NFL career score per game to date, NFL career score per year to date, and NFL games started to date). The two most significant variables are age in upcoming season and NFL career score per year to date, each significant at the 1% level.

Our fitted logistic regression model for whether or not each free agent wide receiver was signed by a team has an R^2 value of 0.098 (significant at the 1% level).

Tab. 3: Tight End Model Summaries

Statistic	Signed vs. Unsigned (logistic)	LN(salary) PFA	NFL Games Started PFA	NFL Career Score PFA	NFLCS per Game PFA	NFLCS per Year PFA	NFL Games Started per Cost PFA	NFL Career Score per Cost PFA	NFLCS per Game per Cost PFA	NFLCS per Year per Cost PFA
Regression Adjusted R-squared	0.152 (not adjusted)	0.184	0.228	0.188	0.331	0.246	0.256	0.188	0.289	0.193
Regression RMSE	0.4304	0.76	14.79	424.66	8.99	125.23	1.98	47.96	1.04	14.63
Number of Variables in Regression	10	6	3	3	9	7	3	3	3	2
Partition R-squared	N/A	0.386	0.273	0.237	0.334	0.378	0.324	0.249	0.396	0.285
Partition RMSE	N/A	0.70	14.11	401.41	8.85	112.71	1.86	44.98	0.95	13.65
Number of Terminal Nodes in Partition	N/A	8	6	5	7	7	6	5	7	6
Variable of Initial Split	N/A	NFLCS/ Game to Date	Age in Upcoming Season	Age in Upcoming Season	NFLCS/ Year to Date	NFLCS/ Year to Date	Age in Upcoming Season	Age in Upcoming Season	NFLCS/ Game per Cost to Date	NFLCS/ Year per Cost to Date

Tab. 4: Wide Receiver Model Summaries

Statistic	Signed vs. Unsigned (logistic)	LN(salary) PFA	NFL Games Started PFA	NFL Career Score PFA	NFLCS per Game PFA	NFLCS per Year PFA	NFL Games Started per Cost PFA	NFL Career Score per Cost PFA	NFLCS per Game per Cost PFA	NFLCS per Year per Cost PFA
Regression Adjusted R-squared	0.098 (not adjusted)	0.325	0.281	0.242	0.419	0.419	0.288	0.235	0.390	0.381
Regression RMSE	0.4537	0.89	15.62	1141.686	17.83	257.97	2.55	182.49	2.78	39.91
Number of Variables in Regression	4	8	8	7	9	10	10	8	8	8
Partition R-squared	N/A	0.474	0.389	0.373	0.478	0.493	0.466	0.418	0.518	0.455
Partition RMSE	N/A	0.77	14.36	1034.88	16.79	238.65	2.13	158.65	2.46	37.24
Number of Terminal Nodes in Partition	N/A	11	8	7	7	10	8	8	9	7
Variable of Initial Split	N/A	NFLCS/ Year to Date	NFLCS/ Year to Date	NFLCS/ Year to Date	NFLCS/ Game to Date	NFLCS/ Year to Date	NFLCS/ Year per Cost to Date	NFLCS/ Year per Cost to Date	NFLCS/ Year per Cost to Date	NFLCS/ Year per Cost to Date

It includes four (of 21 possible) predictor variables: age in upcoming season, NFL games started to date, NFL career score per game to date, and NFL career score per year to date. Of these predictor variables, age in upcoming season and NFL career score per year to date are the most significant (both at the 1% level) just as they are in the model for tight ends.

The logistic regression models for both tight ends and wide receivers suggest that the primary focus of evaluators is average performance per year thus far and how many years a player has left in the league, as measured by age. We also note that NFL games started to date has a negative coefficient in both models, which suggests that among players with similar receiving production and age, those with more starts are less likely to be signed. This likely is due to the fact that players with more games started are likely older and past the prime of their career. Additionally, they likely have taken more of a physical beating in their career and could be more of an injury risk.

Our prediction models for players' salaries after free agency show interesting similarities and differences from the logistic regression models for whether a player is signed or not. In our model for salary, we use the natural log of the player's salary (in thousands) as the outcome variable. Salary data behaves approximately log-normally, so using the log of the salary is a better fit to the assumptions of a linear regression model.

3.2 FREE AGENT SALARIES

The fitted linear regression model for tight end free agent salaries has an adjusted R^2 of 0.184 (significant at the 0.01% level). This model selected six (of 17 possible) predictor variables that are a combination of college performance and NFL performance to date. Specifically, the selected predictors were college receptions, yards, and touchdowns and NFL career score to date, NFL career score per game to date, and NFL career score per year to date. Among these, college receptions and NFL career score per game to date are the only variables not significant at the 10% level. NFL career score per year to date is the only variable significant at the 1% level, indicating that average receiving production to date is the leading indicator for tight end salary.

We see similar results in our fitted recursive partitioning tree model for tight end free agent salary. The tree model has an R^2 of 0.386 and RMSE of 0.695, which improves upon the RMSE of 0.764 for the linear regression model. The first split in the tree uses NFL career score per game to date, which confirms that average NFL receiving productivity is the most important predictor of tight end salary. The tree uses college and NFL performance variables as well as NFL salary to date as the splitting variables in all but one of the tree's eight splits.

Our results for wide receiver free agent salaries echo those for tight ends, though college performance does not appear as frequently in the wide receiver models. The fitted linear regression model for wide receiver free agent salary had an adjusted R^2 of 0.325 (significant at the 0.01% level). Eight (out of 22 possible) predictors were selected: salary to date, BCS indicator, BMI, college touchdowns, college final year touchdown percentage, NFL games started to date, NFL career score per game to date, and NFL career score per year to date. Similar to our models for tight end salary, the most significant (at a 0.01% level) variable for wide receiver salary is NFL career score per year to date.

In this salary model, NFL games started to date has a negative coefficient (significant at the 1% level), just as it did in the logistic regression for whether a wide receiver would be signed or not. This may indicate that players with more games started are seen as a more substantial injury risk in the future, which is factored into a lower expected salary. It is surprising that the BCS indicator variable is included with a negative coefficient in the wide receiver free agent salary model. One possible explanation is selection bias due to the fact that the highest paid players in free agency are often players who were low-draft picks (from non-BCS schools) which outperformed their low-paying rookie contracts, whereas premier players (from BCS schools) are more likely to be re-signed prior to reaching free agency because they will require less of a pay increase from their relatively more expensive rookie contracts. In our sample, only 23% of the non-BCS wide receivers were picked in the first three rounds of the draft, as compared to 58% for BCS wide receivers. Meanwhile, only 10% of the non-BCS tight ends in our sample were picked in the first three rounds, which is very low relative to the mark of 41% for tight ends from BCS schools.

As compared to this regression model, we see generally similar findings in our fitted recursive partitioning tree model for wide receiver free agent salary. The tree model had an R^2 of 0.474 and RMSE of 0.770, which improves upon the RMSE of 0.891 for the linear regression model. The fact that NFL career score per year to date is used as the splitting variable in the first two levels of the partitioning tree confirms the importance of prior NFL productivity. One interesting difference in the tree model is the role of the physical measure BMI. The regression model did include BMI, but it was not significant even at the 20% level. In the tree model, BMI is used in three splits, with lower BMI giving higher predicted salary in each split. This suggests that in free agency, smaller wide receivers (often slot receivers) like Emmanuel Sanders in 2014 will tend to be higher paid. As we discuss later, this may be logical as slot receivers tend to be the best available free agent receivers, as the larger, premier wide outs (like Calvin Johnson, Dez Bryant, Demaryius Thomas, etc.) tend to be re-signed or franchise-tagged before reaching free agency.

In summary, our models for free agent signing and free agent salary have suggested that average NFL receiving performance to date is the most important factor in NFL teams' evaluation of receiver free agents. The age of free agents is found to be important for predicting signing or not, but not important for predicting salaries. We also see that when signing free agent wide receivers, there seems to be a bias towards the smaller but talented slot receivers.

4. PREDICTING FUTURE FREE AGENT PERFORMANCE AND VALUE

We now shift our focus to trying to predict the performance of tight end and wide receivers *after* they have been signed as free agents. We employ several different measures of NFL performance after free agency: NFL games started post-free-agency, NFL career score post-free-agency, NFL career score per game post-free-agency and NFL career score per year post-free-agency. The first two measures are indicative of cumulative performance whereas the latter two measures are indicative of average performance. For the cumulative performance measures, we required three years of post-free agency performance data to attempt to limit the issue of censoring, as there are some players in our data set that have incomplete data since they are still active in the league.

For each of these outcome measures, we create both linear regression and recursive partitioning tree models. In addition, we will also examine the concept of value for each player by dividing each of these outcome measures by the "cost" (log-salary) of each player.

It is important to note that these models are aimed to predict the future performance of free agents at the wide receiver and tight end positions, not the future performance of all players at these positions. Thus, selection bias may lead to certain variables to have some surprising effects, as the best players at these positions are often given contract extensions before they reach free agency.

4.1 PREDICTING NFL GAMES STARTED POST-FREE AGENCY

NFL games started post-free agency is an important measure of NFL performance because it captures aspects of player contribution other than the usual receiving statistics.

A player can be a starter for a team for reasons other than pure receiving: a tight end or wide receiver can also earn a starting job for leadership ability, ability to attract defenders and create space, and blocking ability. As a specific example, Hines Ward did not produce high receiving statistics in the final two years of his career, but he still was a starting wide receiver for the Pittsburgh Steelers due to his ability to block and attract defenders. Additionally, Larry Fitzgerald (who is currently one of the highest paid wide receivers of all time) does not produce receiving stats at the incredible level he did from 2007 to 2011 (when he had 5 straight 1000-yard seasons and had 49 touchdowns in that five year span). However, due to his still respectable receiving production and his impressive blocking ability in both the run game and downfield on pass plays, he continues to start for the Cardinals and earn his high salary.

Our regression linear model for NFL games started post-free agency of tight ends has an adjusted R^2 of 0.228 (significant at the 0.01% level). The model selected three (out of 16 possible) predictors: age, college touchdowns, and NFL games started to date. College touchdowns is significant only at the 10% level while the other two variables are significant at the 0.01% level.

The significance of age and NFL games started to date makes sense as tight ends who have started in the past are likely to start in the future, while a younger player will have more time remaining in his career to start more games. The regression model for the per-cost version of this outcome variable included the same three predictor variables, which suggests these variables are predictors of not only tight end starters, but high value tight end starters.

The recursive partitioning tree model for NFL games started post-free-agency of tight ends shows similar results to the linear regression model. The tree model has an R^2 of 0.273 and a RMSE of 14.11, which improves slightly upon the RMSE of 14.79 for the linear regression model. The first three splits in the fitted tree use age or NFL games started to date, which are also the two significant variables in the linear regression model. The fitted tree for the per-cost version of NFL games started post-free-agency is highly similar.

Overall, these models indicate that post-free agency games started for a tight end can be best predicted by how many games the player has started pre-free-agency and an estimate of how many years the player has remaining in the NFL (as measured by age).

Our regression linear model for NFL games started post-free agency for wide receivers has an adjusted R^2 of 0.281 and selected eight (of 21 possible) predictor variables. Three predictors are significant at the 1% level: these are the Big Ten indicator (positive coefficient), age (negative coefficient), and NFL career score per year to date (positive coefficient). The linear model for the per-cost version of this outcome is similar, with three variables significant at the 1% level: the Big Ten indicator (positive coefficient), age (negative coefficient), and NFL career score per game per cost to date (positive coefficient). Young players from the Big Ten who have the highest average performance pre-free-agency are predicted to start the most games in the future.

The recursive partitioning tree model for NFL games started post-free agency of wide receivers has an R^2 of 0.389 and a RMSE of 14.36, which improves upon the RMSE of 15.62 of the linear regression model. The five highest-level splits in the fitted tree use NFL career score per year to date, BMI, and age as the splitting variables. These are similar findings to the linear regression in that average NFL performance and age are important, but the significance of BMI in the tree is surprising given its absence from the regression model. The fitted tree model suggests that wide receivers with lower BMIs tend to have more games started post-free agency. The fitted tree model for the per-cost version of NFL games started post-free-agency is similar in that the first three levels of splits use NFL career score per year per cost, the Big Ten dummy variable, and BMI.

Overall, it is interesting to find that while age is very important to predicting future games started for both tight ends and wide receivers, previous starting experience is the most important NFL performance predictor for tight ends' projected future games started, while previous average receiving production is most important for wide receivers.

4.2 PREDICTING NFL CAREER SCORE POST-FREE AGENCY

The cumulative measure of NFL receiving performance after free agency that we use as an outcome variable is NFL career score post-free agency. NFL career score post-free agency combines the yards and touchdowns that a tight end or receiver obtains after free agency, which are the primary ways a pass catcher helps their team.

The regression model for NFL career score post-free agency of tight ends has an adjusted R^2 of 0.188 (significant at the 0.01% level). Three (of 16 possible) predictor variables are included in the model: age and NFL career score per year to date (significant at the 1% level) and college yards (significant at the 10% level). The importance of age and average pre-free-agency performance makes sense, as players who produce a high yardage and touchdown total each year and have more years remaining in the league should be expected to have higher cumulative production in their post-free-agency career. The regression model for the per-cost version of this outcome confirms these same selected variables.

The recursive partitioning tree model for NFL career score post-free agency of tight ends confirms the findings of the linear regression model. The partition has an R^2 of 0.237 and an RMSE of 401.41, which is lower than the regression's RMSE of 424.66. All splits in the fitted tree use age or NFL career score per year to date as the splitting variable, which are the two most significant predictor variables in the linear regression. The fitted tree for the per-cost version of this outcome variable is also highly similar, demonstrating that prediction of NFL career score post-free agency and NFL career score per cost post-free agency of tight ends relies primarily on average annual performance and age.

The regression model for NFL career score post-free agency of wide receivers has an adjusted R^2 of 0.242 and selected seven (of a possible 21) predictor variables. The selected variables are highly similar to those selected as predictors of NFL games started post-free agency of wide receivers. In this model, age and NFL career score per game are both 0.01% significant and the Big Ten dummy is the third most significant. The regression model for the per-cost version of this outcome also selects age, NFL career score per game per cost to date, and the Big Ten dummy as the three most significant variables.

The recursive partitioning tree model for NFL career score post-free agency of wide receivers has an R^2 of 0.373 and an RMSE of 1035, which improves upon the RMSE of 1142 of the regression model. The fitted tree shows some differences from the regression model just discussed but is notably similar to the tree model for NFL games started post-free agency. As in the games started tree, this NFL career score tree only uses NFL career score per year to date and BMI as splitting variables for the first three levels. We see that BMI is again an important variable in the tree model but not in regression model, which suggests that BMI has a non-linear relationship with cumulative performance.

The tree model for the per-cost version of this outcome closely emulates the other wide receiver NFL career score post-free agency models. NFL career score per year per cost to date, BMI, and are used as the splitting variables in the first three levels of the tree.

Overall, these findings suggest that in addition to being projected to start the most games in the future, young receivers from the Big Ten who have high average performance in the past will tend to have the best cumulative receiving performance and value in the future.

4.3 PREDICTING AVERAGE NFL PERFORMANCE POST-FREE AGENCY

The outcome measures in Sections 4.1-4.2 were both cumulative measures of post-free agency career performance. We now examine two outcome measures of *average* post-free agency performance: post-free agency NFL career score per game and NFL career score per year. While the per-game performance captures only performance on the field, the per-year performance measure also incorporates how many games played, which can be impacted by injury or suspension. If a player is injury prone or has off-field issues which leads to suspension, that will affect their performance per year but not performance per game.

These average measures will be especially relevant to teams signing players to short-term contracts where high average productivity is needed more than high cumulative productivity. In this section, we will focus our analysis on models for the per-game outcome and mention some differences from the models for the per-year outcome, as they show similar results.

The linear regression model for the NFL career score per game post-free agency of tight ends has an adjusted R^2 of 0.331 (significant at the 0.01% level). Nine variables (of a possible 16) were selected: age plus eight variables consisting of a mix of college and NFL performance to date. Interestingly, the four variables significant at the 5% level are all college performance variables (college yards per reception, college receptions, college yards, and final year college reception percentage). However, the model for the per-cost version of this outcome model selected three variables: age, NFL games started to date, and NFL career score per year per cost to date. Of these, NFL career score per year per cost to date is the most significant (at the 0.01% level). In total, these results seem to indicate that despite college performance being a good predictor of per-game performance, the key predictor of per-game "value" for tight ends is their per-year value in the past.

The recursive partitioning tree model for NFL career score per game post-free agency of tight ends has an R^2 of 0.334 and an RMSE of 8.85, which improves slightly on the RMSE of 8.99 for the regression model. This tree model uses NFL career score per year to date as the initial splitting variable, but the remainder of the tree uses a mix of physical and college performance variables. The fitted tree model for the per-cost version of NFL career score per game has more focus on per-game value in the past as a predictor of future per-game value, with NFL career score per game per cost to date being the splitting variable in the first two splits of that tree.

It seems that both models for per-game value rely more on average value in the past, while the models for per-game performance include a wider variety of predictor variables. For the tight end per-year performance models, we find a similar result to those of the per-game models, as the college performance predictors are still significant. Per-year performance to date is the most significant predictor of future per-year performance in that model.

Summarizing these models for tight ends, we find that for predicting average performance there are a variety of factors (especially college) that have predictive power in addition to average performance in the past, but for predicting average value after free agency, average value in the past is the most important predictor.

Our regression model for NFL career score per game post-free agency of wide receivers has a relatively high adjusted R^2 of 0.419. This model selects nine (of 21 possible) predictors, four of which are significant at the 1% level: age, the BCS indicator, career college yards, and NFL career score per game to date. Age and average performance to date continue to show significance, while the other two variables are not as important in earlier models. The BCS dummy was included in both of the games started and cumulative NFL career score regressions, while the college yardage measure was not included in either. College measures appear to provide an indication of average performance, but not career length, as they are less present in the models for the cumulative outcomes. Thus, college performance provides an indication of future NFL performance, but not necessarily of career length.

The model for the per-cost version of NFL career score per game of wide receivers has one difference in the most important predictors: a college measure was replaced with weight with a negative coefficient, indicating that the smaller wide receiver free agents provide higher average value. This is an interesting finding since, while we found that small receivers tend to be paid more, we have also now found them to provide more value, indicating they are more than worth the higher pay.

The recursive partitioning tree model for NFL career score per game to date has a R^2 of 0.478 and RMSE is 16.79, which is a slight improvement upon the RMSE of 17.83 for the regression model. The first two levels of the tree use NFL career score per game to date and NFL career score per year to date as the splitting variables, indicating past average performance is the most important predictor of future average performance. The third level includes college yards and BMI as splitting variables, which provides a further indication that college performance is important for predicting average professional performance. BMI continues to be included in our tree models but not the linear regression models. The tree model for the per-cost version of this outcome measure is generally similar with one notable difference: weight was used for a second-level split in the tree, indicating weight's importance in predicting average value.

Our regression model for predicting wide receiver per-year performance shows a single difference from the per-game performance models: the college performance measures are no longer significant, as college performance likely has less predictive value for the number of games missed in a season. The recursive partition tree (shown in Fig. 1) has average performance to date as the first two splits and we also see smaller players (low BMI and low weight) have better predictions.

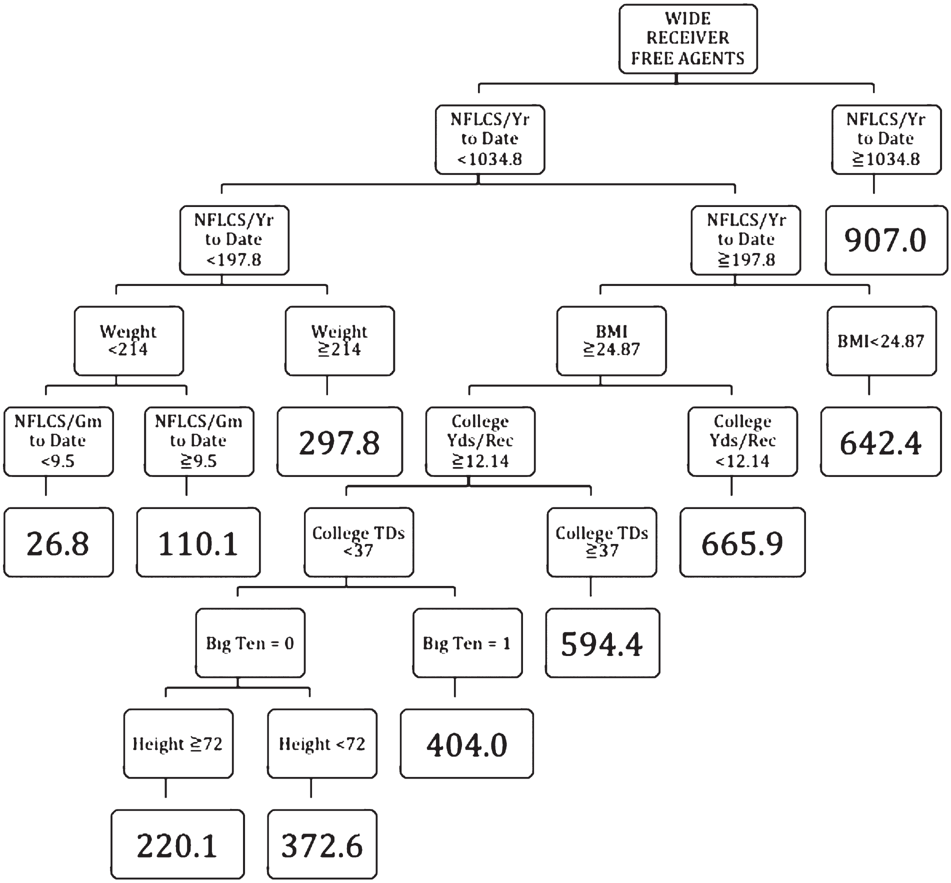

Fig. 1: Fitted recursive partitioning tree with post-free-agency NFL career score per year for wide receivers as the outcome variable. The number in the final node indicates the average expectation of players that would fall into that node.

5. COMPARISON OF SALARY AND PERFORMANCE MODELS

In this section, we compare the variables that are most predictive of free agent signing and salary to the variables most predictive of future performance in order to evaluate whether NFL teams are focusing on the most important factors in their decision-making process.

Overall, our models tend to do better predicting average performance than cumulative performance and do better predicting wide receivers than tight ends, as seen by the higher adjusted R^2 values. It makes sense that average performance is easier to predict, as cumulative performance is also impacted by the extra variability in career length.

Among the models for predicting future wide receiver performance, two predictor variables appear more consistently than all of the others: age and NFL career score per year to date. NFL career score per year to date is the first splitting variable in the majority of the partition trees. A player who is younger will have more years remaining in the league, and if they have higher per-year performance in the past, they are more expected to perform at a high level in the future.

It is interesting to note that age is not included in the regression model for predicting salary (as seen in Fig. 2). This indicates that NFL teams tend to overpay veteran players relative to their performance, as age is negatively correlated with performance of free agents.

The BCS indicator variable also plays an interesting role in our analyses. For wide receivers, the BCS indicator is negatively correlated with future performance in our prediction models. This may seem counterintuitive since many of the best players in the NFL come from BCS conferences. A likely explanation is selection bias: as mentioned earlier, our study is focused entirely on free agents, and many of the best NFL players don't reach free agency but rather are franchise tagged (with a one-year high salary contract) or signed to long-term contract extensions by their team. The top wide receiver free agents tend to be players who exceeded expectations. Players who come from schools outside the BCS tend to be late round draft picks or undrafted free agents who obtain low pay rookie contracts, as shown earlier. Wide receivers who perform well in this subset will then become some of the best free agents available. For tight ends, this effect is not as extreme, likely because tight ends are usually paid less and so they are more affordable.

Alongside the non-BCS players with the best projections in the wide receiver models are those from the Big Ten. In these models, the Big Ten dummy is consistently included with a positive coefficient, and is 5% significant in the two cumulative performance models. However, after performing an influence analysis, we find that taking out influential observations[2] leads to the Big Ten dummy no longer having 5% significance in any of the four post-free agency performance models. The most influential observation is Derrick Mason (who went to Michigan State University). Mason left the Tennessee Titans in free agency in 2005 at the age of 31 and went on to start 94 of 96 games for the Baltimore Ravens over the next six seasons, including four seasons with over 1,000 receiving yards.

Another interesting observation is that in the wide receiver models for the average performance outcomes, weight is consistently negative and is very significant

[2] observations with Cook's distance greater than a $\frac{4}{n \times k \times 1}$ cutoff, where n is the number of observations in the model and k is the number of input variables

in the average value models. This result is surprising given that many of the top receivers in the NFL over the past decade have been larger receivers, such as Calvin Johnson, Brandon Marshall, Dez Bryant, Demaryius Thomas, A.J. Green, Larry Fitzgerald, and Andre Johnson. However, note that only one of these top receivers (Andre Johnson) reached free agency, and it was not until he had spent 12 years in Houston. The other six are still with the team that drafted them or were traded (Brandon Marshall).

Teams tend to give the top outside wide receivers lucrative extensions before they reach free agency, so that these players do not leave their original teams. It is the smaller receivers (often lining up in the slot) who become some of the top free agents, such as Emmanuel Sanders leaving the Steelers and joining the Broncos in 2014, Wes Welker leaving the Patriots and joining the Broncos in 2013, Danny Amendola leaving the Rams and joining the Patriots in 2013, or Derrick Mason leaving the Titans and joining the Ravens in 2005.

For tight ends, meanwhile, we discovered that size has no significance in predicting future salary, performance, or value. Height, weight, and BMI were not included in any of the 9 models for salary, performance, and value of tight ends. However, it was included in the model for predicting whether tight ends would be signed (though with low significance).

We also find that, while college receiving statistics are not important for projection of wide receiver free agents in the NFL, they do have some significance in prediction of future performance of tight end free agents. This may be due to the fact that, in the NFL, wide receivers are targeted more frequently than tight ends (on almost every team). This results in lower overall performance from tight ends, which makes it harder to differentiate some tight ends based on past NFL performance alone. Therefore, college statistics seem to be acting as a supplement to the NFL performance to date predictor variables.

In **Table 5**, we evaluate the extent to which the variables that are currently important to evaluation of tight end and wide receiver free agents in the NFL are similar to the optimal predictor variables selected in our models. Specifically, we compare the adjusted R^2 of our linear regression models for future performance using either (1) the optimal predictors selected for that future performance measure or (2) the predictors selected as most predictive of free agent salary. The extent to which these two sets of predictors disagree is suggestive of inefficiency in evaluation of free agents by NFL decision makers.

In Table 5, we see that NFL teams are closer to the optimal adjusted R^2 level in the average performance measures, especially when considering wide receivers. NFL decision makers are less close to the optimal adjusted R^2 level for the cumulative measures of performance (and for tight ends), which indicates greater uncertainty in evaluation of long-term performance. Thus, it is optimal for NFL teams to sign wide receiver free agents to short-term contracts to minimize the impact of the uncertainty in the ability of the player to sustain their performance.

Tab. 5: Comparison of adjusted R^2 of the models that we created (using optimal variables) versus the adjusted R^2 of models created for the given post-free agency (PFA) outcome variable using the variables selected as most predictive of players' salaries. Thus, a smaller gap between the corresponding adjusted R^2 values would indicate more efficiency (in terms of paying players the efficient salary for their production).

Optimal Predictors vs. Salary Selected Predictors	Tight Ends		Wide Receivers	
	Adjusted R^2 With Optimal Variables	Adjusted R^2 using Ln(salary) selected Variables	Adjusted R^2 With Optimal Variables	Adjusted R^2 using Ln(salary) selected Variables
NFL Games Started PFA	0.228	0.086	0.281	0.148
NFL Career Score PFA	0.188	0.119	0.242	0.154
NFL Career Score per Game PFA	0.331	0.251	0.419	0.406
NFL Career Score per Year PFA	0.246	0.153	0.419	0.393

In Fig. 2, we examine the specific differences between the selected predictors for NFL career score per year post-free agency and Ln(salary) post-free agency for wide receivers. As seen in Table 5, this particular comparison is one where the salary-selected predictors do almost as good of a job of prediction as the optimal-selected predictors. Thus, we see a large overlap in the set of predictors in the Venn diagram, though additional variables such as age and weight seem to be underemphasized by evaluators.

6. PREDICTING FUTURE APPROXIMATE VALUE (AV) OF FREE AGENTS

To evaluate whether our NFL performance measures (NFL games started, NFL career score, NFL career score per game, and NFL career score per year) are appropriate indicators of tight ends' and wide receivers' contributions to their teams, we have also created'stepwise regression models to predict a player's approximate value (cumulative and per year) after free agency. Approximate value

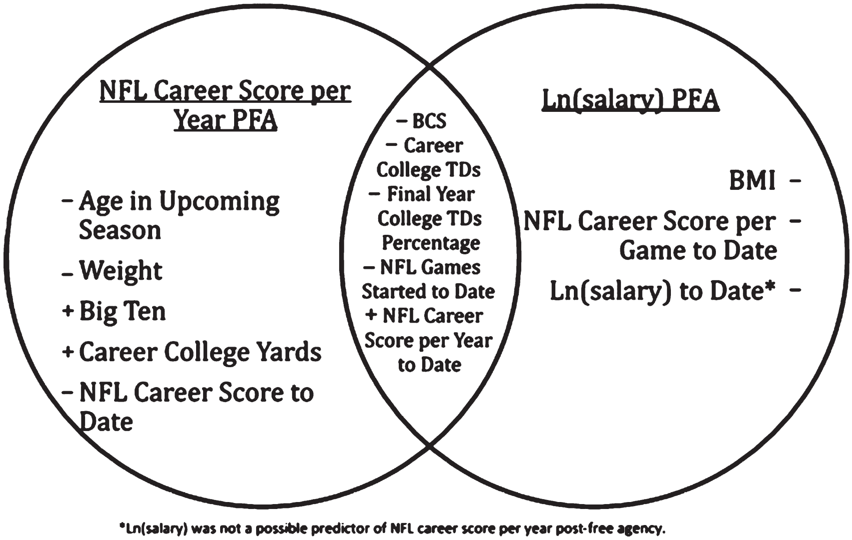

Fig. 2: Venn diagram comparing the selected variables from linear regression models for (1) NFL career score per year post-free agency as the outcome versus (2) natural logarithm of salary post-free agency as the outcome variable. A "+" indicates that the variable is included in the model with a positive coefficient, while a "–", indicates that the variable is included with a negative coefficient.

(AV) is a measure that Pro Football Reference uses as their "attempt to put a single number on each player-season since 1950" ("Football glossary and football statistics glossary," 2000-2016).

Our models for tight end AV and AV per year post-free agency each include two predictor variables and have adjusted R^2 values of 0.195 and 0.204, respectively. Each of these models includes age (with a negative coefficient) and one of the two measures of average NFL performance to date (NFL career score per game or per year). Meanwhile, age and average NFL performance to date are consistently among the most significant predictors of our NFL performance post-free agency indicators.

For wide receivers, our AV and AV per year post-free agency models include a wider variety of predictor variables, but still show similar results to our models for future (post-free agency) performance of wide receivers. These models have adjusted R^2 values of 0.225 and 0.368, respectively. Despite the inclusion of a wider variety of predictor variables, we again find that the age (with a negative coefficient) and a measure of average performance to date are the most significant predictors (both are 0.01% significant in both models), which was also the case when modeling our NFL performance post-free agency indicators for wide receivers.

Given the similar results provided by these models for prediction of the future approximate value of free agents, the indication is that our NFL performance and value post-free agency measures are appropriate measures of the contributions that tight ends and wide receivers provide for their teams.

7. SUMMARY AND DISCUSSION

In this paper, we have presented statistical models for predicting the signing, salary and future performance of NFL tight end and wide receiver free agents. Our predictive modeling strategies were logistic regression, ordinary least squares regressions, and recursive partitioning decision trees. These models have shown that the most important variables for predicting the future performance of tight end free agents include age, average annual receiving performance, number of NFL games started, and some college performance variables. Meanwhile, the most important variables for predicting the future performance of wide receiver free agents include age, average annual receiving performance, the BCS college indicator, and the player's weight.

We found that average performance is easier to predict than cumulative performance, both in terms of lower overall prediction errors as well as greater agreement between the optimal predictors of future average performance and the optimal predictors of free agent salary. There is greater disagreement between the predictors of future cumulative performance and the predictors of free agent salary.

For tight ends, our results display one key inconsistency between predictors of future performance and salary. The player's age is included with a negative coefficient in all four future performance regression models and three of the four value (performance per cost) models, though it does not appear in the salary model. Therefore, NFL teams are overpaying older tight ends relative to their expected future performance.

There seems to be an overpayment for older wide receivers, as well. All eight of the performance and value regression models for wide receivers include age with a negative coefficient, while yet again, it does not appear in the salary model. Players who sign a contract lasting five or six years with a high salary beginning in their players' primes and continues until they are in the later stages of their careers could influence this finding.

We also identified a disparity between prediction of future wide receiver free agent performance and salary.

We find that smaller receivers are projected to have better performance and value than their larger counterparts (weight appeared with a negative coefficient in all average performance and value regression models and BMI – favoring a lower value - appeared in all of the performance and value partitions). Meanwhile, weight and BMI are not significant for prediction of salary, as weight does not appear in the model and BMI is not even significant at the 20% level.

Separately, it is interesting to note that there are some variables that change in sign (positive versus negative impact) depending on the outcome variable. For example, consider NFL games started to date for tight end free agents. Those who have more games started to date are more likely to be signed and have a higher expectation of expected starts in the future, but are projected to have lower average performance (using both average performance measures: NFL career score per game and NFL career score per year). This is could be due to the fact that a player with many starts in the past is an experienced veteran in the league and will likely continue to be a starter in the future, but also those with more starts have been in the league longer. Thus, they are likely past their prime and will tend to have lower average performance than they had produced in their prime.

We present one final case study when our model would have suggested a better decision. Brandon Jones and Brandon Lloyd were two free agent receivers in 2009. Jones signed a contract with San Francisco, paying him $2.6 million that year, while Lloyd signed a contract with Denver, paying him just over $500,000 that year. Our models projected Jones, who was 27 at the time, to start only 7.6 more NFL games and to have an NFL career score post-free agency of 450.5. In the end, Jones appeared in 8 games that year and had one catch for 18 yards. He never appeared in an NFL game again. On the other hand, Lloyd was projected to start 23.6 games and to have an NFL career score of 1620.8. Brandon Lloyd since then has exceeded these expectations with 44 starts and an actual NFL career score post-free agency of 4141.3 by his retirement at the end of the 2014 season. Lloyd was paid less than Jones in 2009, but was projected to perform better by our models. In the end, he definitely had a better post-free agency performance, as our models predicted.

It is important to note several limitations of our approach. We only use quantitative predictors, but it is important to take qualitative aspects into consideration to adjust predictions, such as a player's injury history, off-field problems, and the depth chart with new team.

We believe that paired with an analysis of these qualitative factors, our quantitative models can improve the precision in predicting future performance of tight end and wide receiver free agents in the NFL. We also believe that these modeling strategies can be applied to other NFL positions, assuming a similar set of variables can be established to be predictive of future performance.

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APPENDIX

Here we will explore in detail some of our model predictions for the 2014 wide receiver free agent class. We focus on this group of 67 wide receiver free agents in the NFL in 2014 as they had a variety of intriguing storylines and a larger sample than that of tight ends. There were a few receivers who had experienced some success and were looking to continue that success elsewhere, while there were many looking to prove their skills.

Desean Jackson had a breakout year in the 2013 season, his sixth season in the NFL. He accumulated 82 catches for 1332 yards and 9 touchdowns. These were career highs in catches and yards, and tied his career high in touchdowns. His 1332 yards put him as the ninth leading receiver in the NFL. After the Eagles cut Desean, he was quickly signed by the Redskins to the highest average cap hit deal given to a wide receiver that offseason. Our models projected Desean to have the best performance in this class in our average performance measures, including NFL career score per year post-free agency, which our model projected him to have 890.5. In his first six seasons, Desean's NFL career score per year to date was 1122.4. Our projected decrease in average performance likely came from the fact that it was questionable how many more years Desean would be in his prime, as he turned 28 years old in the 2014 season. In the first two years of this deal, Desean achieved an NFL career score per year of 945, which is slightly higher, but not too far from our projection of 890.5.

The next highest paid free agent receiver in the 2014 offseason was Eric Decker. Decker had shown consistently strong performance over the prior two seasons, especially in 2013, as he nearly reached 1300 yards. After signing with the Jets, people wondered if Decker could continue his high performance with an inexperienced quarterback, Geno Smith, after his past years with Peyton Manning. According to our models, Decker was projected to have the best cumulative performance after free agency of all of this year's wide receiver free agents and the second highest NFL career score per year post-free agency of 808.6. Decker achieved an NFL career score per year of 1158.55 from 2014 to 2015, including a 1000-yard season in 2015 when paired with Brandon Marshall, as Ryan Fitzpatrick took over at quarterback for the Jets. It remains to be seen if Decker's average post-free agency performance will fall toward his projection after he passes out of his prime years, but his fit as the number two receiver in Chan Gailey's offense has helped him beat his projection thus far.

Two younger free agent receivers who were looking to take another step in their careers were Golden Tate (former Seahawk) and Andre Roberts (former Cardinal). Tate received substantial attention from the Seahawks Super Bowl run in the 2013 season. Potentially as a result of this attention, despite the fact that Tate only had 72 more yards than Roberts over the first four years of their careers, Tate was given a five-year contract with an average cap hit of $6.2 million per year, while Roberts was given a four-year contract with an average cap hit of $4 million. Roberts, though, was projected to perform better in the future by our models. However, we acknowledge that this projection did not account for the fact that Tate was entering a better situation as the number two receiver to Calvin Johnson in Detroit with Matt Stafford at quarterback, while Roberts became the number three receiver behind Desean Jackson and Pierre Garcon in Washington with a questionable quarterback situation.

If we were to adjust our projections due to these situations, we would have adjusted Roberts down from the NFL career score per year post-free agency of 808.2, while for Tate, we would have adjusted up from the NFL career score per year post-free agency of 489.6. In the end, these adjustments would have been appropriate, as Tate had a breakout season in 2014 and has an NFL career score of 1168.5 for the 2014 and 2015 seasons, while Roberts achieved a NFL career score of 322.3 due to his status on the depth chart and the Redskins' quarterback problems, as he is now primarily used as a kick returner.

While Tate and Roberts were the notable young receivers in this class, Steve Smith was the notable older receiver. Smith spent 13 years as a Carolina Panther, including 5 years as a pro bowl player. He even led the NFL in catches, receiving yards, and receiving touchdowns in 2005. For the first time in his NFL career, at age 35, he played for a team other than the Carolina Panthers. Our models projected that Smith would be in the top ten in the average performance categories in this group of 67, but not in the top ten in cumulative performance, which clearly makes sense as he does not have too many years left in the NFL. In the end, Smith has been productive for the Ravens, accumulating an NFL career score per year of 954.35, relatively high as compared to his projection of 590.2.

Kenny Britt was another interesting storyline in this wide receiver group. While he did not get much attention from the media, the St. Louis Rams were quick to sign Britt. This signing marked the reuniting of Britt with coach Jeff Fisher who originally drafted Britt to the Titans in 2009. Britt had injury problems over the three years prior to free agency, along with multiple violations of the personal conduct policy resulting in a suspension. His performance fell sharply after a promising first two years in the league, and Fisher likely believed he could return Britt to his past level of play. Our model projected Britt to have an 80% chance of being signed and an unexpectedly high NFL career score per year post-free agency of 577.1 (given he had an NFL career score of only 96 for the 2013 season). Our model expected him to recover somewhat from his past few years of disappointment, but probably not to come all the way back to his performance level in 2009 and 2010. In the end, Britt has been productive as our models indicated, even surpassing our model's prediction to achieve an NFL career score per year of 772.4 over the 2014 and 2015 seasons.

Overall, these projections were relatively accurate or were made inaccurate by factors that we were able to point out prior to the season (such as the depth chart situations that Tate and Roberts entered). However, it is important to note that our projections were not just for this season, but were instead for the remainder of each player's career. It will be interesting to see if these players trend more towards our projections moving forward.