The NFL's House Money: How Compensatory Draft Picks can Allow Teams to tap into a Player Rental Market

In October 2018, the Los Angeles Rams traded a 2019 3rd and 5th round draft picks for Dante Fowler Jr. of the Jacksonville Jaguars. This exchange represents the 4th time in three years the Rams traded for former 1st round draft picks on expiring contracts.[1] While the Rams gave up a significant amount of draft capital to acquire Fowler, Watkins, Cooks, and Peters as a potential one year rentals, the Compensatory Draft Selection process might explain how the Rams took a smaller hit than apprehended with draft capital. In this piece, I will focus on how NFL teams can strategically use the Compensatory Draft Pick process to only give up less than a perceived loss at the time of the trade. This short exercise will operate with the assumption the reader is familiar with the Compensatory System, NFL Draft Value, and other functions of the National Football League.

Given the current Compensatory Draft Pick system, I sought to look at how teams can project which players will receive high-end compensatory picks down the road. The main proposition I investigated is if a team can determine how the APY number—the key factor in compensatory draft picks—is calculated, then a NFL organization can trade for players who are likely future candidates of the compensatory system. *See* OTC discussion about APY and Compensatory Draft Picks.[2] Accordingly, if a team traded a 2nd round pick for a player, then the lost draft value would not solely be a 2nd round draft pick. Instead, the lost draft value would simply be the gap between the exchanged pick and the future compensatory pick. While this proposition would delay draft picks by a year, it allows a team an insurance policy and the ability to "rent" players.

A good example of this Sammy Watkins. If one viewed the Watkins trade solely in 2017, the Rams received a net loss of (327) in trade value. *See* Exhibit 1. However, when viewing the entire picture, one can see the Rams in reality face a net loss of (211). Even if the cost of lost draft capital is still felt, there is a sense the damage is not as bad as one initially perceived because of the role of compensatory draft picks. Further, the Rams got on field production from Watkins while assessing if Watkins was a quality fit for their offense. As a result, organizations can learn to play with the NFL's "house money" to leverage trades while benefitting from short-term rentals.

Exhibit 1

Year	BUF Rec'd	LAR Rec'd
2017	EJ Gaines & 2018 2nd Rounder	Sammy Watkins & 2018 6th Rounder
2018 Draft Value	340	13
2018	None	2019 3rd Round Compensatory Pick
2019 Draft Value	None	116
Net	327	(211)

To assess this proposal, I first needed to understand what factors determine a player's APY. I initially began by scrapping contract data off of OTC. After obtaining each player's contract information,

[1] In 2017, the Rams traded E.J. Gaines and a 2018 2nd round pick for Sammy Watkins and a 2018 6th round draft pick. In 2018 the Rams traded 2019 2nd and 4th round draft picks with the KC Chiefs for Marcus Peters and a 2019 6th round pick. In 2018, the Rams traded a 2019 1st round draft pick with the New England Patriots for Brandin Cooks.

[2] https://overthecap.com/projecting-the-2019-compensatory-picks/

including their APY, I wanted to build out a profile of factors which would help one determine why the player got paid the amount they did. The idea here is if one calculated which factors determine our output (APY), then one could look at these factors for potentially predicting future APY.

Here, I pulled a list of 15-20 relevant factors for two major position groups: Wide Receiver and Defensive Line. Further, I focused on the top 50 players from these two position groups to focus my sample size on players who would be eligible for higher end compensatory picks. Finally, I cut off all rookie contracts from the APY calculation because these player's APY is limited to the rookie allocation, and as a result don't represent best APY for the compensatory system.

After creating a profile for the top 50 players, I ran linear regression models with a Frontline Solver platform. Linear regression is a tool of predictive analysis which examines how well predictor variables do in determining an outcome variable. Further, this tool can assess if the variables are statically significant. Here, I looked at if factors like draft position, height, pro statistics, and college attended helped determine a player's APY. After multiple rounds, I ended up with the following results:

Exhibit 2: Wide Receivers

Metric	Value
Residual DF	6
R2	0.9743116
Adjusted R2	0.79449278
Std. Error Est	1861758.29
RSS	2.0797E+13

Coefficients

Predictor	Estimate
Draft Positio	15898604.4
Draft Round	13847735.5
Catch %	5734824.47
TD	138569.994
AV	68572.4654
Rec	-11586.8426

Exhibit 2:Defensive Line

Metric	Value
Residual DF	4
R2	0.97512446
Adjusted R2	0.69527464
Std. Error Estimate	2164847.12
RSS	1.8746E+13

Coefficients

Predictor	Estimate
Draft Position	11564862.73
Draft Round	11177167.19
FF	130445.1586
AV	127753.7581
QBHits	50466.94988
Solo	14316.27835
TFL	-74023.39824
G	-155035.584

These results indicate one can explain 79% and 69%--shown by the adjusted R2—of APY variance with the variables show in the coefficient box. While the sample size is relatively small, this still implies a strong relationship (97% R2) between certain statistical categories and explaining a player's eventual contract value. One of the biggest conclusions from this analysis is it implies the NFL Free Agent market relies on statistics to determine why teams pay players. In turn, the free agent market implicitly is not an irrational one subject to random deals where players without strong statistical backgrounds get paid at the top of the market. As a result, a NFL team can use this conclusion to trade for players on future expiring contracts with stronger statistically backgrounds with the assurance there is an increased likelihood this player will receive a top end contract and thus netting a comp. pick.

After establishing which stats matter for each position group, a Front Office would look at which players thrive in these categories, anticipate any pending FAs, and look to acquire those players. See Exhibit 3, 4. While the best players are not surprisingly locked into long term deals, the wide receiver market does show players currently playing on their rookie contracts who might obtain big contracts down the road. As a result, this makes certain players candidates to trade for in anticipation of a possible compensation pick down the road. The logic would be to determine if a FO or coaching staff is tired of a player and willing to swap the player for a trade pick. For example, if the Jets FO is upset with Robby Anderson's off field behavior, he might be a great candidate to trade for, let play, and potentially let walk down the road to return a compensation draft pick. Similarly, if the Eagles feel Nelson Agholor is replaceable after the DeSean Jackson acquisition, then he would be a quality match. A similar process can be applied for defensive line positions.

The next step for a Front Office would be to replicate the analysis and determine which statistics possess predictive power for the other position groups. After this, a GM would yield the ability to potential target rental players using future draft picks knowing the acquired player is likely to bring compensatory draft picks down the road if the player based on his statistical background.

Exhibit 3: Wide Receiver Stats for Key Variable

Player	Age	Pos	Ctch%	TD	Y/G	Draft Round
Davante Adams*	25	WR	0.636333	35	72.63333	2
DeAndre Hopkins*+	25	WR	0.591667	28	83.26667	1
Mike Evans*	24	WR	0.566667	25	81.53333	1
Tyreek Hill*+	23	WR	0.694667	25	69.46667	5
Michael Thomas*+	24	WR	0.769333	23	80.46667	2
Brandin Cooks*	24	WR	0.640333	20	72.06667	1
Stefon Diggs*	24	WR	0.703	20	66.06667	5
Amari Cooper*	23	WR	0.61	19	62.56667	1
Jarvis Landry*	25	WR	0.652667	17	64.56667	2
Odell Beckham*	25	WR	0.6095	16	86.55	1
JuJu Smith-Schuster*	21.5	WR	0.7015	14	77.3	2
Sterling Shepard	24	WR	0.646	14	54.56667	2
Marvin Jones	26.5	WR	0.552	13	65.4	5
Robby Anderson	24.5	WR	0.5425	13	56.25	UDFA
Nelson Agholor	24.5	WR	0.6565	12	47	1
Robert Woods	25	WR	0.664	12	62.83333	2
Tyler Lockett	25.5	WR	0.724	12	47.5	3
Alshon Jeffery	26.5	WR	0.514	11	58.85	2
Cooper Kupp	24.5	WR	0.6935	11	64.35	3
Tyrell Williams	24.5	WR	0.6015	11	55.85	UDFA

Exhibit 4: Defensive Line Stats for Key Variables

Player	Age	Pos	G	FF	Solo	TFL	QBHits	Round
Aaron Donald*+	26	D-Line	15.33333	11	109	57	99	1
Yannick Ngakoue	22	D-Line	16	10	69	29	70	3
Frank Clark	24	D-Line	15.66667	7	77	31	66	2
Leonard Williams	23	D-Line	16	2	85	25	64	1
DeForest Buckner	23	D-Line	15.66667	1	132	29	60	1
Jadeveon Clowney	24	D-Line	15	4	119	53	59	1
Trey Flowers*	24	D-Line	15	5	100	25	59	4
Chris Jones	23	D-Line	16	6	74	29	52	2
Danielle Hunter*	23	D-Line	16	2	110	44	49	3
Demarcus Lawrence	25.5	D-Line	16		77	29	49	2
Khalil Mack*+	25.5	D-Line	16		115	29	48	1
Stephon Tuitt	24	D-Line	13.33333	3	74	23	46	2
Za'Darius Smith	25.5	D-Line	15		41	13	41	4
Grady Jarrett	24	D-Line	15.33333	3	82	27	38	5
Deatrich Wise	23.5	D-Line	16		31	10	35	4
Olivier Vernon*	26.5	D-Line	14		69	23	35	3

Vic Beasley	25	D-Line	15.33333	7	71	26	28	1