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The Sunk-Cost Fallacy in the National Football League: Salary Cap Value and Playing Time

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Abstract

The National Football League (NFL) draft is used to examine the presence of the sunk-cost fallacy in teams' playing time decisions. In the NFL, salary cap value represents a significant sunk cost to teams. We use the structure of the NFL draft to conduct a fuzzy regression discontinuity design. Optimal bandwidth local linear results suggest a 10% increase in salary cap value yields an additional 2.7 games started, for players selected near the cutoff between the first two rounds. Despite being no more productive, the first round selections receive a compensation premium, which leads to them starting significantly more games.

Keywords

sunk-cost fallacy, salary cap value, NFL, NFL draft

Introduction

The sunk-cost fallacy is a decision-making bias that arises when non-recoverable costs influence future decision making. Neoclassical economics dictates that sunk costs should be ignored, as optimal decision making considers only marginal costs and marginal benefits. However, there is evidence that sunk costs do bias real-world decisions. We examine the role of sunk costs in playing time decisions made by

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National Football League (NFL) teams. If sunk costs are significant determinants of playing time, teams may be operating inefficiently.

The majority of sunk-cost fallacy evidence has come from lab and field experiments involving small stakes or hypothetical actions (Arkes, 1996; Arkes & Blumer, 1985; Bazerman, Beekun, & Schoorman, 1982; Garland, 1990; Kogut, 1990; Moon, 2001; Staw, 1976). For example, Arkes and Blumer (1985) randomize the price of season tickets to a university's theater. Individuals paid US$15 (the normal price), US$13, or US$8. They found people who paid more attended more shows. However, since the price was randomly assigned, optimal decision making would predict all three groups attend the same number of shows. Staw (1976) evaluates hypothetical decisions regarding the allocation of funds to different divisions within a technology firm. Individuals choose to allocate money to either consumer products or industrial products. They are then presented with 5-year performance information for the two divisions and asked to allocate additional funds. The results show a significant escalation of commitment to the previously chosen division.

Observational studies of the sunk-cost fallacy have focused on professional sports, specifically the National Basketball Association (NBA; Camerer & Weber, 1999; Leeds, Leeds, & Motomura, 2015; Staw & Hoang, 1995). Professional sports provide a unique opportunity to study the sunk-cost fallacy as there is an abundance of consistently recorded data on employees, managers, and owners and the stakes are very high. One of the initial investigations of the sunk-cost fallacy using observational data was conducted by Staw and Hoang (1995). In their study, they consider a player's selection number in the NBA draft as a sunk cost and find it has a significant effect on playing time and survival. Camerer and Weber (1999), using the same sunk cost, explore several alternate explanations and find a smaller and less robust sunk-cost effect in the NBA. However, the use of selection number in both studies is potentially problematic as it is also a measure of expected future success, or potential; something considered by Staw and Hoang (1995), but much more thoroughly by Camerer and Weber (1999).

Finally, Leeds, Leeds, and Motomura (2015) use sharp regression discontinuity (RD) on the cutoff between the two rounds of the NBA draft and find no evidence of the sunk-cost fallacy for playing time in the NBA. They discuss two potential differences between first and second round selections in the NBA draft. First, the NBA collective bargaining agreement (CBA) fixes rookie salaries based on selection number for players selected in the first round. Second round players' salaries are determined by negotiations between teams and players' agents. Therefore, there is, potentially, a larger financial commitment to first round selections. However, they do not directly estimate the effect of compensation on playing time. Second, they mention a possible psychological bias that first round picks are much more valuable. However, they do not thoroughly discuss the proposed bias and they do not consider if there is a difference between the way first round selections and the first player chosen by a team are viewed, since first round players are not always the first player chosen by their team.

We evaluate the possibility of the sunk-cost fallacy affecting playing time in the NFL. We consider financial commitment to rookie players as a sunk cost. We analyze the first two rounds of the NFL draft, using a similar method to Leeds et al. (2015). Evaluation of the sunk-cost fallacy in the NFL draft is important for two major reasons. First, all players prior to 2011, who we study, had their salaries freely negotiated. Second, Keefer (2014), using sharp RD, found a very large and robustly significant discontinuity in rookie compensation between the first and second rounds. Freely negotiated compensation and the established effect of the rounds on compensation provide the ideal situation to quasi-experimentally test for the existence of the sunk-cost fallacy. We conduct fuzzy RD to directly examine the effect of compensation, a sunk cost, on playing time.

Institutional Framework

NFL Draft

NFL teams select amateur players in a seven-round format. The worst team in the previous season has the rights to select first in each round. Selections within a round follow the order of previous year team success. That is to say, the best team in the previous season has the rights to the 30 second selection in each round, as there are 32 NFL teams. Even though each team has the rights to one selection per round, teams trade selections; therefore, it is common for teams to select multiple times or not at all in a given round. In fact, in 2009, four teams selected twice in the first round and seven teams selected at least twice in the second round. Once drafted, teams own the rights to a player for one year. If no agreement between the two sides is reached, a player may reenter the draft the following year. The NFL draft takes place after the free agency period each year, during which current players without a contract may negotiate with teams.[1]

Massey and Thaler (2013) and Keefer (2014) found the NFL draft was subject to heuristic thinking. Massey and Thaler (2013) analyzed trades to determine if the NFL was accurately pricing selections in the draft. They found the market was valuing first round selections irrationally high. In other words, to receive a first round selection in a trade teams were giving up selections, which, in total, were of far greater value. Keefer (2014) examined the effect of the rounds on rookie compensation by examining discontinuities in compensation at the round cutoffs. Since the rounds are simply groupings of selections, they should not discontinuously impact the compensation of drafted players when selection number is considered. However, sharp RD estimates show the discontinuity between the first two rounds to be US$240,000, or 36% of the average salary for the first selection in the second round.[2]

Compensation in the NFL

In the NFL, a salary cap governs player compensation; the sum of each team's players' salaries must be less than a specified dollar amount. The NFL salary cap is a hard cap; teams are not allowed to exceed the dollar amount. This is different than other professional sports leagues, such as the NBA, that have soft salary caps; teams can exceed the cap but must pay a luxury tax for doing so. The NFL's salary cap is calculated as a percentage of previous season league revenues, which is collectively bargained between the NFL owners and the NFL Players Association. A player's salary cap value is the sum of his base salary, incentive bonuses, and signing bonus pro-rated for the life of his contract.[3] It is important to note that salary cap value is determined before a season and cannot change during a season. The NFL uses a proprietary formula to determine how much of each team's salary cap can be used to sign rookie players, the rookie allocation. The equation is part of the CBA and there is no attempt to suggest how the rookie allocation is distributed with teams (NFL, 2006). We use salary cap value as the measure of rookie compensation, the sunk cost, due to the amortization of signing bonuses. The salary cap value represents a significant sunk cost to teams. The amount of money dedicated to one player is directly debited from the team's total allotment available to spend on rookies.

Method

Ideally, one would have a sample of players of equal productivity and randomly assign higher compensation to one group then analyze the difference in the number of games started between the groups. In practice, compensation cannot be experimentally manipulated; however, the NFL draft creates a natural experiment that we analyze using fuzzy RD. Keefer's (2014) results show that first round players selected near the round cutoff receive a very large wage premium. Since the round a player is selected in, for players selected near the round cutoffs, is essentially randomized, the first round wage premium can be used to identify the effect of compensation on the number of games started.

For fuzzy RD the local average treatment effect (LATE) is defined as the ratio of the discontinuities in the number of games started and compensation.

$$\text{LATE} = \frac{\lim\limits_{S \to c^+} E[G|S] - \lim\limits_{S \to c^-} E[G|S]}{\lim\limits_{S \to c^+} E[\ln w|S] - \lim\limits_{S \to c^-} E[\ln w|S]}, \tag{1}$$

where G is the number of games started, S is selection number, c is the cutoff between rounds, and w is compensation. The LATE can be consistently estimated using the two-stage least squares (2SLS; Imbens & Lemieux, 2008; Lee & Lemieux, 2010; van der Klaauw, 2002). The initial method is to use pooled cubic regression (Imbens & Lemieux, 2008; Keefer, 2014; Lee & Lemieux, 2010; Leeds et al., 2015; van der Klaauw, 2002).

$$\ln w_n = \alpha + \tau R_n + \sum_{i=1}^{3} \beta_i \tilde{S}_n^{\,i} + \sum_{i=1}^{3} \lambda_i R_n \tilde{S}_n^{\,i} + X_n \gamma + \varepsilon_n, \tag{2}$$

$$G_n = \pi + \rho\, \widehat{ln\ w_n} + \sum_{i=1}^{3} \chi_i \widehat{S}_n^{\,i} + \sum_{i=1}^{3} \delta_i R_n \widehat{S}_n^{\,i} + X_n \vartheta + \mu_n, \tag{3}$$

Where R is a binary variable for second round selections, $\tilde{S}$ is selection number centered at the round cutoff, $\tilde{S} = S - c$, and X is a vector of control variables. The coefficient ρ is the sunk-cost effect identified via fuzzy RD. Here Equation (2) is analogous to the sharp RD estimated in Keefer (2014).

However, the pooled method may be biased by the use of observations far from the round cutoff. Therefore, we use local linear regression, estimating 2SLS on a specified bandwidth, h, such that $-h \leq \tilde{S} \leq h$.[4,5]

$$\ln w_n = \alpha + \tau R_n + \beta \tilde{S}_n + \lambda R_n \tilde{S}_n + X_n \gamma + \varepsilon_n \tag{4}$$

$$G_n = \pi + \rho\, \widehat{ln\ w_n} + \chi \tilde{S}_n + \delta R_n \tilde{S}_n + X_n \vartheta + \mu_n. \tag{5}$$

We use the Imbens and Kalyanaraman (2012) method of calculating the optimal bandwidth. The optimal bandwidth is estimated to be 8.414, since selection number is discrete we use 8.0. Since the selection of bandwidth can have an impact on the results, we report estimations for $h = 6, 8, 10$.

The validity of RD relies on individuals on either side of the cutoff being essentially the same. Lee (2008) shows that if individuals cannot be precisely manipulated into the treatment or control group, then treatment is randomized for a bandwidth near the cutoff. There may be some manipulation, however, imperfect manipulation satisfies the validity of the RD strategy. In the NFL draft, players cannot be precisely manipulated into one group or another. Prospects have the incentive to manipulate themselves to being selected in the first round. If prospects could perfectly manipulate themselves, the density of first round selections would be much greater than second round selections. However, due to the structure of the NFL draft, the density of players is equal on either side of the cutoff, ensuring imperfect manipulation by prospects.

Another test for the validity of the RD strategy is analyzing productivity between rounds. Berri and Simmons (2011) find that players, specifically quarterbacks, selected early in the NFL draft are not more productive than their later round counterparts. Also, Massey and Thaler (2013) and Keefer (2014) report evidence that players selected close in the NFL draft have essentially equal performance, on average. Therefore, the RD strategy allows us to look at the number of games started for players who are equal in productivity but with one group receiving a substantial wage premium.

Testing for the exchangeability of players in our sample requires a cross-position measure of productivity. Therefore, we use the defense-adjusted value over average (DVOA) calculated by Football Outsiders (2014). DVOA measures a player's per play value over an average player of the same position in the same game situations. Unfortunately, the measure only applies to offensive-skilled positions, therefore,

Table 1. Variable Definitions.

Variables	Definitions
Games Started	The number of games started
Ln(Cap Value)	Natural logarithm of salary cap value
Round 2	Binary variable for second round selections
Selection #	Selection number in the NFL draft
Wins	The number of team wins in the previous season
Within team selection #	Binary variables for a player's within team selection number
All-American	Binary variable for consensus collegiate All-American selections
Collegiate division	Binary variables college division (FBS automatic qualifying, FBS nonautomatic qualifying, FCS, other)
DVOA	Defense-adjusted value over average
Year	Binary variables for the year
Team	Binary variables for the team
Position	Binary variables for a player's position

Note. DVOA = defense-adjusted value over average; NFL = National Football League; FBS = football bowl subdivision; FCS = football championship subdivision.

limiting our sample. We estimate Equation (2) using DVOA as the dependent variable to determine if there are any significant differences in productivity between rounds.

As shown in Equations (1–5) we use the natural logarithm of salary cap value as our sunk cost.[6] The vector of control variables, X, contains player and team-related information and year fixed effects. We control for position fixed effects as transitioning from college football to the NFL may be relatively easier for certain for positions. Furthermore, we include a vector of binary variables indicating the player's collegiate division and whether the player was selected as a consensus All-American. Many second round selections are not the second player chosen by teams, therefore, it is important to control for the distinction between the round a player is chosen in and his within-team selection number. As a result, we include a series of binary variables indicating a player's within-team selection number. Team-related information includes team fixed effects. Also, due to the structure of the draft, players chosen early within a round are, on average, selected by worse teams. Therefore, we control for the success of a player's team by including the number of previous season wins and the number of wins squared. We include the quadratic term to allow for flexible specification, since team quality has an impact on the number of opportunities a player has to start. Table 1 lists all variables and their definitions.

Data

The data cover all players drafted in the first two rounds of the NFL draft from 2002 to 2009. In 2002, the NFL expanded to 32 teams by adding the Houston Texans. In

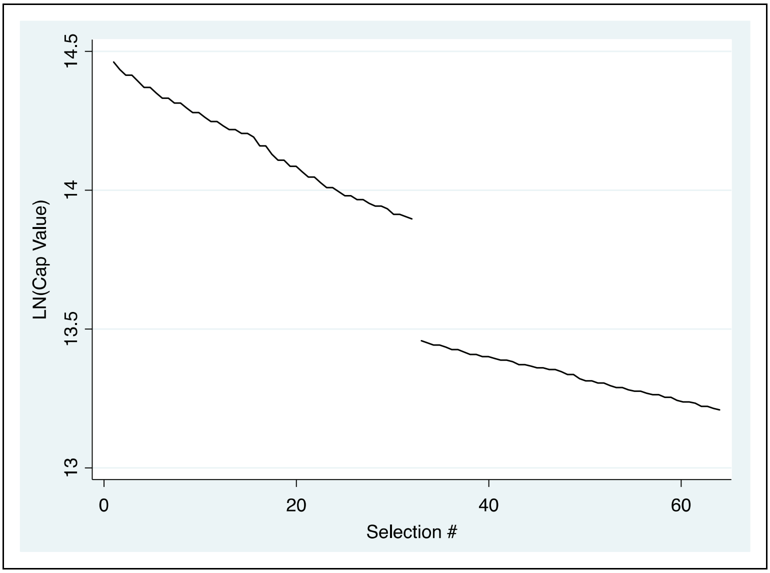

Figure 1. Average compensation by selection number, bandwidth = 15.

2009, the NFL owners decided to opt out of the remaining years of the CBA making 2009 the final season under these guidelines (NFL, 2008). The length of the data was decided based on these two factors.

Salary cap values were collected from the *USA Today* (2011), which maintains a database of professional athletes' salaries. The mean of our dependent variable, *LN(Cap Value)*, for the full sample is 13.75 with a standard deviation of 0.508. The number of games started and position were collected from the NFL (2011). The average number of games started is 6.838 with a standard deviation of 6.096. Selection number, round, year, team, within-team selection number, collegiate division, and All-American status were collected from Pro Football Reference (2011).

Results

Graphical Results

Figure 1 displays the average compensation, calculated using a bandwidth of 15, by selection number for the first two rounds. It is clear that there is a discontinuity between the rounds. Since other individual and team factors, such as position and team quality, have an impact on the number of games started, we follow Lee and Lemieux (2010) and residualize *Games Started*. We regress *Games Started* on the vector of control variables and calculate the residuals, which represent the variation in *Games Started* not explained by the control variables.

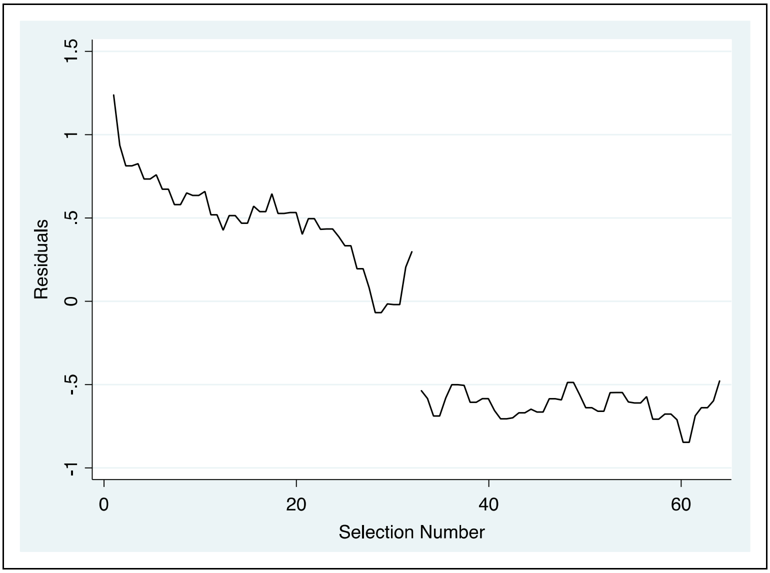

Figure 2. Average residualized games started by selection number, bandwidth = 15.

$$G_n = \pi + X_n\varphi + \upsilon_n$$
$$\hat{\upsilon}_n = G_n - \hat{\pi} + X_n\hat{\varphi}$$

Figure 2 displays the average residualized variable, using a bandwidth of 15. There appears to be a large downward shift from round one to round two.

Estimation Results

We begin by analyzing DVOA to test the exchangeability of players. Regressions for DVOA are presented in Table 2. In all specifications, there is no significant discontinuity between rounds. The lack of a significant difference between rounds supports our treatment of players on either side of the cutoff as being exchangeable. However, one drawback to the approach is the inability to employ local linear estimation due to the reduced sample size of only offensive-skilled players. The results also seem to support Berri and Simmons (2011) in that draft position does not significantly predict offensive skilled position productivity.

Pooled cubic results are reported in Table 3. The discontinuity in compensation between the first and second rounds is highly significant and estimated to be –0.321, or 38%, which is consistent with Keefer's (2014) estimate of 36%. The difference is due to Keefer (2014) estimating the discontinuity in untransformed salary cap value and the inclusion of All-American status and collegiate division. Column (2) reveals compensation to be a significant determinant of the number of games started. The coefficient for *Ln(Cap Value)* is 13.87, which implies a small change of 7% in salary

Table 2. DVOA Results.

Variables	(1)	(2)	(3)
Round 2	−0.680 (1.667)	−0.782 (1.732)	−0.797 (1.767)
Selection #—33	0.440 (0.348)	0.444 (0.359)	0.443 (0.354)
(Selection #—33)^2	0.0349 (0.0269)	0.0358 (0.0280)	0.0360 (0.0280)
(Selection #—33)^3	0.000682 (0.000540)	0.000711 (0.000565)	0.000721 (0.000569)
Round 2* (Selection #—33)	−1.045 (0.649)	−0.972 (0.638)	−0.938 (0.625)
Round 2* (Selection #—33)^2	0.0280 (0.0409)	0.0205 (0.0416)	0.0184 (0.0422)
Round 2* (Selection # −33)^3	−0.00229* (0.00136)	−0.00216 (0.00134)	−0.00214 (0.00133)
Wins	−0.940 (0.662)	−0.967 (0.676)	−0.944 (0.670)
Wins^2	0.0473 (0.0329)	0.0482 (0.0336)	0.0469 (0.0333)
All-American			0.799 (0.695)
Collegiate division	No	Yes	Yes
Within team selection #	Yes	Yes	Yes
Fixed Effects	Year, team, and position	Year, team, and position	Year, team, and position
Constant	12.16 (9.325)	11.01 (9.302)	11.00 (9.318)
Observations	144	144	144
R^2	.445	.448	.456
Adjusted R^2	.127	.114	.116

Note. DVOA = defense-adjusted value over average. Robust standard errors in parentheses.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

cap value yields an additional game started. Since there are only 16 regular season NFL games, an additional game started is very significant. Also, a change of 7% in compensation is relatively small, especially when compared to the substantial premium at the cutoff between rounds. Another way to put the results in perspective is to calculate the elasticity of games started with respect to salary cap value, $\eta = \frac{\hat{\rho}}{G}$. The elasticity is 2.03; any percentage change in salary cap value yields a double the percentage change in the number of games started.

To check the robustness of our results, we include a direct measure of NFL productivity. Since NFL positions have different measures of productivity it is not possible to use standard measures. Therefore, we employ the DVOA, limiting our sample to offensive-skilled positions. Estimations including DVOA are reported in Table 3. Including DVOA does not significantly change the results, the coefficient for *Ln(Cap Value)* is 14.16 and highly significant.

However, as mentioned in the Method section, pooled regression results may be biased by the inclusion of observations far from the cutoff. Local linear results for bandwidths of 6, 8, and 10 are reported in Table 4. For compensation, the

Table 3. Pooled Cubic Results.

Variables	Ln(Cap Value)	Games Started	Ln(Cap Value)	Games Started
Round 2	−0.321*** (0.0469)		−0.468*** (0.105)	
Ln(Cap Value)		13.87** (6.995)		14.16** (7.163)
Selection #—33	0.0107* (0.00596)	0.629* (0.361)	0.0363** (0.0139)	0.355 (0.476)
(Selection #—33)^2	0.00157*** (0.000477)	0.0356 (0.0226)	0.00304*** (0.000976)	0.0375 (0.0333)
(Selection #—33)^3	7.59e−06 (1.08e−05)	0.000892* (0.000535)	3.01e−05 (1.96e−05)	0.00114 (0.000718)
Round 2* (Selection #—33)	−0.0186* (0.0104)	−0.547 (0.489)	−0.0136 (0.0250)	0.879 (0.840)
Round 2* (Selection #—33)^2	−0.00216*** (0.000767)	−0.0350 (0.0294)	−0.00527** (0.00200)	−0.132*** (0.0479)
Round 2* (Selection #—33)^3	5.40e−06 (1.67e−05)	−0.000882 (0.000761)	7.88e−06 (3.99e−05)	0.00100 (0.00123)
Wins	−0.00800 (0.00997)	0.0437 (0.407)	−0.0248 (0.0209)	0.413 (0.724)
Wins^2	0.000649 (0.000610)	−0.0151 (0.0261)	0.00174 (0.00131)	−0.0426 (0.0453)
All-American	−0.0101 (0.0132)	0.708 (0.689)	0.0218 (0.0319)	0.354 (0.977)
DVOA			−0.00351 (0.00317)	0.0278 (0.0995)
Collegiate division	Yes	Yes	Yes	Yes
Within team selection #	Yes	Yes	Yes	Yes
Fixed effects	Year, team, and position	Year, team, and position	Year, team, and position	Year, team, and position
Constant	13.96*** (0.0826)	−184.2* (96.17)	14.02*** (0.154)	−191.7* (98.08)
Observations	506	506	144	144
R^2	.961	.234	.976	.456
Adjusted R^2	.956		.960	

Note. DVOA = defense-adjusted value over average. Robust standard errors in parentheses.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 4. Local Linear Results.

	$h = 10$		$h = 8$		$h = 6$	
Variables	Ln(Cap Value)	Games Started	Ln(Cap Value)	Games Started	Ln(Cap Value)	Games Started
Round 2	−0.219*** (0.0511)		−0.244*** (0.0599)		−0.299*** (0.0724)	
Ln(Cap Value)		18.92* (10.26)		26.67** (10.72)		16.82** (8.305)
Selection #—33	−0.0104*** (0.00334)	0.257 (0.288)	−0.00638 (0.00602)	0.970*** (0.332)	−0.000706 (0.0101)	0.120 (0.456)
Round 2*(Selection #—33)	−0.00569 (0.00772)	0.190 (0.381)	−0.00755 (0.0111)	−0.856* (0.503)	0.00299 (0.0259)	−0.878 (0.971)
Wins	−0.00272 (0.0166)	0.0942 (0.770)	0.00122 (0.0179)	0.517 (0.845)	−0.00856 (0.0253)	0.451 (0.844)
Wins^2	0.000596 (0.000916)	−0.0222 (0.0466)	0.000484 (0.00105)	−0.0528 (0.0481)	0.00115 (0.00136)	−0.0655 (0.0516)
All-American	0.0100 (0.0362)	0.681 (1.339)	0.0164 (0.0391)	−0.941 (1.589)	−0.0129 (0.0440)	1.451 (1.589)
Collegiate division	Yes	Yes	Yes	Yes	Yes	Yes
Within team selection #	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Year, team, and position	Year, team, and position	Year, team, and position	Year, team, and position	Year, team, and position	Year, team, and position
Constant	13.91*** (0.127)	−259.4* (140.7)	14.09*** (0.0962)	−366.3** (148.9)	13.98*** (0.115)	−229.6** (112.6)
Observations	158	158	126	126	110	94
R^2	.887	.385	.877	.394	.866	.592

Note. Robust standard errors in parentheses. Bandwidth denoted as *h*.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5. Percentage of Plays Local Linear Results.

Variables	$h = 12$	$h = 10$
Ln(Cap Value)	0.471* (0.285)	0.962** (0.399)
Selection #—33	−0.0146 (0.0116)	−0.0129 (0.0130)
Round 2*(Selection #—33)	0.0518*** (0.0184)	0.0818*** (0.0250)
Wins	−0.0391 (0.0555)	−0.0960* (0.0498)
Wins^2	−0.00114 (0.00319)	0.00161 (0.00294)
All-American	0.00555 (0.0686)	−0.0132 (0.0761)
Collegiate division	Yes	Yes
Within team selection #	Yes	Yes
Fixed effects	Year, team, and position	Year, team, and position
Constant	−5.426 (3.858)	−12.37** (5.453)
Observations	70	58
R^2	.828	.790

Note: Robust standard errors in parentheses. Bandwidth denoted as *h*.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

discontinuity between rounds is highly significant for all bandwidths. The discontinuity ranges from 24.5% to 34.9%. For the number of games started, the coefficient for *Ln(Cap Value)* ranges from 16.82 to 26.67. For the optimal bandwidth, $h = 8$, the coefficient is 26.67 and is significant to the 5% level. All else equal, a 10% increase in salary cap value yields an increase of 2.7 games started. The optimal bandwidth coefficient implies an elasticity of 3.88, at the mean of *Games Started*. Using the optimal bandwidth local linear estimates, the change in the number of games started at the cutoff between rounds, moving from selection number 32 to 33, is –5.71, all else equal.

To test the robustness of the results, we examine an alternative measure for playing time. We use the percentage of offensive or defensive plays a player actually played. This provides a more fine-grained measure of player utilization. The number of plays for each player was collected from Pro Football Focus (2014) but is only available since 2007. The number of offensive and defensive plays was collected from the NFL (2011). The correlation between the number of games started and the percentage of plays is 0.88, supporting our use of the number of games started as a measure of commitment and player utilization. However, we conduct local linear regression for the percentage of plays for comparison. Considering the reduced sample size, we present local linear estimates for the percentage of plays using bandwidths of 10 and 12. The results are reported in Table 5 and show compensation is significant in both cases. A 10% increase in compensation increases the percentage of plays by 5 to 10 percentage points.

Considering the pooled cubic and local linear results, there is a significant effect of compensation on playing time for drafted NFL rookies. Players selected in the first round receive significantly higher salaries. As a result, first round players start significantly more games. The evidence suggests the sunk-cost fallacy is present in NFL labor allocation decisions.

Conclusion

The relationship between compensation, a sunk cost, and playing time is analyzed using fuzzy RD on the natural experiment created by the NFL draft. The effect of the round in which a player is chosen, which is effectively randomized near the round cutoff, on compensation is used to conduct 2SLS estimations of the number of games started. Salary cap value is a significant determinant of the number of games started in both pooled cubic and local linear regressions. Pooled cubic results imply an increase of 7% in salary cap value yields an additional game started or an elasticity of 2.03. Local linear regression on the optimal bandwidth, calculated using the Imbens and Kalyanaraman (2012) method, suggests a 10% increase in salary cap value results in 2.7 additional games started, or an elasticity of 3.88. The results are also robust to the inclusion of performance measures and when examining the percentage of offensive or defensive plays a player played.

Despite being no more productive, first round selections chosen near the cutoff between the first two rounds of the NFL draft receive a very large wage premium of approximately 30% compared to their second round counterparts, which leads to them starting significantly more games. The results show NFL teams do consider sunk costs, salary cap value, when making playing time decisions. The fact that NFL teams consider sunk costs when determining playing time may suggest that other firms also consider sunk costs when allocating their labor, even when the decisions are for very high stakes. However, further research is needed on the persistence of the sunk-cost fallacy. Staw (1976) shows that people are much less likely to exhibit the fallacy when others incurred the sunk cost. Therefore, we would expect the effect of compensation on playing time to be much less when there is a change in management or coaching.

The results differ from recent research using the NBA, which suggests sunk costs are irrelevant in playing time decisions (Leeds et al., 2015). The different results may point to an important factor about the sunk-cost fallacy. In the NBA, first round draftees cannot freely negotiate their compensation. However, in the NFL, prior to 2011, drafted players' compensation was freely negotiated between teams and agents. Our results support the idea that increased financial commitment may bias future decisions. However, it may be the case that the bias from increased financial commitment is only present when the financial commitment is not exogenously determined. In other words, sunk costs may only be relevant when the decision maker is responsible for incurring the sunk costs. The difference in results may support Bazerman, Beekun, and Schoorman (1982) who found an escalation of commitment to hypothetical employees only when the decision maker was directly responsible for previously promoting the individual.

When the previous promotion was made by a third party, there was no escalation of commitment.

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Notes

1. The NFL draft also has compensatory selections. Compensatory selections are added to the end of rounds, usually late rounds. However, since compensatory selections do not affect the cutoff between rounds one and two, we restrict our discussion. A full description of compensatory selections may be found in the NFL CBA (NFL, 2006).
2. The round effects are also shown to be robust to year, team, position, team success, and within team selection number.
3. Unlike other professional sports, NFL player contracts are not guaranteed. The only part of an NFL contract that is always guaranteed is the signing bonus, as it is paid at the origination of the contract.
4. This is equivalent to using the rectangle kernel on the limited sample. Cheng, Fan, and Marron (1997) discuss the use of the triangle kernel for boundary data. However, Imbens and Lemieux (2008) and Lee and Lemieux (2010) suggest the rectangle kernel, as kernel choice is a minor issue in practice. Using the triangle kernel the results were not significantly different. Estimation results using the triangle kernel are available from the author.
5. We also estimated local cubic regression on the specified bandwidths. The results are robust to these specifications and are available from the author.
6. The analysis was also conducted using untransformed salary cap value with similar results. The results from these estimations are available from the author upon request.

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