ELSEVIER

Journal of Economics and Business 60 (2008) 536–550

Journal of Economics & Business

Allocation of scarce resources: Insight from the NFL salary cap

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Received 18 January 2007; received in revised form 19 August 2007; accepted 21 August 2007

Abstract

We examine the effects of variations in player compensation on NFL franchise performance from 1994 to 2004. Evidence shows that team success depends significantly upon both the actual and perceived fairness of pay distribution. Specifically, proficiency relative to that of competitors is high when compensation inequity across players, whether justified or unjustified, is low. This result suggests that franchises taking a superstar-approach to personnel decisions perform worse on average, most likely because of the dissatisfaction generated among relatively low-paid teammates.

JEL classification: G39; J31

Keywords: NFL; Compensation; Performance

1. Introduction

The relationship between pay and performance is a central issue in finance and economics research. In his seminal work, Lazear (1989, 1991) shows that when pay is distributed relatively evenly among employees, cooperation increases and firm efficiency improves. Most subsequent empirical research has focused on publicly traded corporations. Since these firms report compensation data in accordance with SEC requirements, corporate salary data are readily accessible, and the value of these data is enhanced by the availability of an observable performance metric in the form of stock returns.

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doi:10.1016/j.jeconbus.2007.08.002

Labor markets in professional sports provide a comparable environment and also a suitable performance metric in the form of team wins. Thus, researchers have increasingly utilized sports markets to shed light on topics such as agency problems (Atkinson, Stanley, & Tschirhart, 1988), racial discrimination (Kahn, 1992), contract negotiations (Conlin, 1999), and talent evaluation (Hendricks, DeBrock, & Koenker, 2003; Massey & Thaler, 2005). Professional sports leagues also provide a valuable opportunity to quantify the cost/benefit tradeoffs of hiring highly talented individuals.

Because the number of players on professional sports franchises is capped, teams may receive disproportionate returns to talent. Rosen (1981) shows that large rents accrue to talented players because, for instance, from a team's perspective having one very talented quarterback is preferable to having several average quarterbacks. As within-team talent often varies widely, the relationship between wage inequality and team performance is potentially important because large disparities in player pay may disrupt team cohesion.

However, Berri and Jewell (2004) examine National Basketball Association (NBA) franchises and find that salary dispersion is not a significant determinant of team wins, and hypothesize that player salary and performance are not highly correlated. In a related study, DeBrock, Hendricks, and Koenker (2004) use performance data from Major League Baseball (MLB) to examine wage 'fairness,' defined as compensation that can be explained by performance. They, on the other hand, find that franchises with relatively low wage dispersion perform better, yet find little support that fairness is a significant determinant of team success.

While the NBA and MLB have 'soft' salary caps, the National Football League (NFL) imposes a relatively strict salary restriction upon all franchises. This constraint was initiated by the Collective Bargaining Agreement (CBA) starting with the 1994 season. The presence of this 'hard' cap generates a good opportunity to study organizational decision making under constrained resources.[1] That is, team management is forced to abide by a fixed salary budget and therefore must formulate a distribution scheme that retains the best talent while simultaneously ensuring that players feel fairly compensated.

Our goal is to determine how limited resources are best allocated under the constraints of the CBA. In similar spirit, Leeds and Kowalewski (2001) contrast the strength of the relationship between pay and performance before and after the imposition of the NFL salary cap, and find that the compensation is more strongly determined by productivity in the free agency era. While we also examine the link between player pay and performance, we focus mainly on this relationship at the unit (*e.g.*, offensive and defensive) and team levels.

We begin by estimating justified (fair) player compensation using an extensive series of performance and experience variables. We then examine the impact of variations in levels of justified pay, unjustified pay, and unjustified dispersion in pay on offensive and defensive unit proficiency. Finally, we examine the influence of intra- and inter-team variations in salary distribution across roster positions on franchise success. Section 2 discusses the measurement of compensation differences and the design of two regression models used to examine the relationship between incentives and performance. Results are provided in Section 3, and Section 4 contains conclusions and final remarks.

[1] Even beyond any potential application to traditional labor markets, studies exploring the NFL labor market are potentially fruitful because of the significant value of NFL franchises. According to NFLPA documents (NFL Players Association, 2003), in 2003 the aggregate value of all 32 NFL franchises was US$ 20,104,000,000. Television rights contracts for the 1998 through 2005 seasons are estimated to be worth US$ 2.2 billion per season.

2. Data and methodology

We compile individual player compensation data and productivity statistics for each NFL season from 1994 to 2004. Compensation data consist of yearly base and bonus pay while productivity data consist of a series of offensive and defensive player performance statistics, and we supplement these metrics with date of birth, draft round, games started, games played, and games injured. The combined data consist of 19,256 player-year observations. Team performance statistics include defensive and offensive points allowed and scored for 2696 NFL regular season games from the 1994 season through the 2004 season. The sources for player salaries are the *USA Today Library and Research Service* and the website of the *NFL Players' Association* (NFLPA.org). Player and team performance statistics are obtained from *Stats, Inc*. and *Pro Football Edge* respectively. Player injury data is gathered from JT-SW.com.

The ultimate goal of this study is to determine in what manner and to what degree compensation allocation decisions affect team proficiency in the NFL. For instance, some franchises may choose to retain a group of superstar players and supplement these high-priced athletes with low-priced support players, thus creating an environment characterized by a high degree of compensation inequality. Other teams may decide to distribute wealth more evenly, with mid-level talent dominating the roster and relatively few stars and low-level players rounding out the organization. Such personnel decisions are important because football, like basketball, is a sport in which team cohesion is crucial to success. If players feel underpaid relative to others, then they are less likely to cooperate with teammates and coaches.

Most of the observed pay dispersion is likely to be fair because highly productive players deserve more money. So, throughout the analysis, we differentiate between justified (fair) and unjustified (unfair) compensation. Justified pay can be explained by player productivity while unjustified pay cannot. We first identify the most readily observable factors that determine player wages, and then calculate the amount of compensation that each player receives which can or cannot be explained by these determinants. We propose that the levels and distributions of justified and unjustified compensation will be significant determinants of both unit (defensive and offensive) proficiency and team win rate.

2.1. Player performance and compensation

We begin our analysis by measuring the relationship between player compensation and productivity while correcting for draft and playing experience variables. The pooled time-series cross-section OLS regression model, which includes season fixed effects, is specified as follows:

$$C_{it} = \alpha_0 + \alpha_1 \mathrm{PROD}_{it} + \alpha_2 \mathrm{DRAFT}_i + \alpha_3 \mathrm{EXP}_{it} + \varepsilon_i, \tag{1}$$

where C_{it} is the natural log of injury-adjusted compensation (either base or bonus pay) for player i in year t.

Teams must pay players even when they are unable to play due to injury. When a player is injured, his performance level is zero, and therefore would appear to be overpaid relative to his contribution. Implementing an injury correction is important because we later impute unfair pay, and any excess compensation resulting from injury is unlikely to constitute injustice in the eyes of teammates. The injury adjustment is as follows:

$$C_{it} = \frac{\mathrm{Pay}_{it}(16 - \mathrm{Games\ Injured}_{it})}{16}, \tag{2}$$

where Pay is the amount of compensation received by player i in season t and Games Injured is the number of games that player i is unable to play in season t due to injury.[2]

PROD_{it} is a vector that includes single-season statistical productivity variables and a dummy variable indicating whether a player is a starter.[3] DRAFT_i includes the dummy terms *Undrafted* (1 if the player was not drafted; 0 otherwise) and *Round 1* (1 if the player was drafted in the first round; 0 otherwise). EXP_{it} includes the terms $Age < 25$ (1 if player age is less than 25; 0 otherwise) and $Age > 30$ (1 if player age is greater than 30; 0 otherwise), GS, GP, GS^2, GP^2, and Pro Bowls.[4,5] The GS (previous career games started) and GP (previous career games played) terms capture returns to experience while the GS^2 and GP^2 terms capture potential increasing or decreasing rates of returns to experience. Pro Bowls reflects the total number of times the player was named to the league's all-star game.

We regress base and bonus pay separately and then use the resulting estimates to calculate each player's explained base and bonus compensation in each season. Rather than combining the two forms of compensation, we choose to treat them individually because of important differences. Signing bonuses are particularly valuable to players because they are generally made in advance by a year or more in anticipation of future performance. In contrast, teams can avoid paying the base salaries of those players whose performance is below that expected by simply terminating their contracts.

2.2. Team performance and compensation

Earlier we proposed that the means and dispersions of unjustified compensation should be negatively correlated with team performance. The latter may occur because teammates become resentful of a perceived injustice, and this resentment adversely affects team cohesion. The former may be important because teams with high levels of unjustified spending are likely to be wasting resources. That is, if some players are overpaid relative to their capacity to contribute, then because of strict compensation limitations imposed by the salary cap, the team is less free to acquire or retain other talent.

When modeling unit and team proficiency as a function of pay, we use μ, σ, and Gini to measure team compensation differences relative to the league average.[6] Because we normalize these terms, there is both an intra-team an inter-team component to each metric. The μ and σ terms measure the mean and dispersion, respectively, of unexplained compensation. Each is computed separately for starters (μ_S and σ_S) and backups (μ_B and σ_B) in order to isolate how variations in pay among these two groups affect organizational performance. Gini, unlike σ, measures intra-team compensation dispersion (also relative to the league-wide average) regardless of whether or not variations in player performance merit these differences.

To calculate μ, we first solve (1) and then estimate each player's justified compensation. We next calculate each player's unjustified pay, which is defined to be the difference between justified

[2] Player injury data is available from 1995 to 2004.

[3] A starter is defined to be a player who starts at least 75% of the games in a season.

[4] We measure age using dummy variables because a multicollinearity problem arises when using a linear age term. Main results remain intact when age (either discrete or linear) is removed altogether.

[5] Productivity variables are single-season performance statistics while game experience variables are summed over the course of players' careers.

[6] The Gini coefficient is calculated by dividing the area between a Lorenz curve (a plot of cumulative wealth vs. cumulative population) and the 45° equality line by 0.5. A perfectly uniform distribution of player salary would result in a Gini coefficient of zero, while a Gini coefficient of one represents total inequality.

and observed compensation, and compute the average unjustified compensation allotted to each team unit (*e.g.*, defensive or offensive). Finally, we subtract the league-wide average unjustified unit pay (to obtain a normalized metric) and take the natural log. Teams with high μ terms are the most likely to be wasting resources (paying too much for too little performance).

While the means of unjustified spending are captured by μ, dispersions in unjustified spending are captured by σ. To compute σ we solve (1), calculate the intra-team standard deviation of unexplained pay, and again normalize by the league-wide average unit standard deviation. Teams with high σ terms exhibit more variation in unjustified compensation than the league-wide mean, and thus are particularly likely to have poor team cohesion.

The Gini metric, unlike μ and σ, does not utilize (1), but rather is computed simply from observed intra-team compensation differences relative to league-wide averages. Thus, Gini reflects the relative degree to which an organization values star players. Teams with high Gini have taken a superstar approach to personnel decisions; relatively few players earn a relatively large proportion of the total team payroll. One goal of this study is to determine whether such a strategy is wise.

Combining these metrics, the resulting pooled time-series cross-section regression model that we use to quantify the relationship between compensation and team performance is:

$$\begin{aligned} P_{\text{it}} = {} & \alpha_0 + \alpha_1 \text{POS}_{it} + \alpha_2 \text{Gini}_{it} + \alpha_3 \mu_{\text{S}it} + \alpha_4 \sigma_{\text{S}it} + \alpha_5 \mu_{\text{B}it} \\ & + \alpha_6 \sigma_{\text{B}it} + \alpha_7 \text{Injuries}_{it} + \varepsilon_i, \end{aligned} \tag{3}$$

where P_{it} is team *I*'s performance (*e.g.*, *Defensive Points Allowed*, *Offensive Points Scored*, or *Wins*) in season *t*.[7] As described above, each right-hand-side variable except for *Injuries* measures the normalized value for team *i* (the difference in between the value for team *i* and the league-wide average value) in season *t*. The variable Injuries is the number of player-games lost to injury by each team in each season. This adjustment is important because as the number of injuries increases, performance is likely to decrease. We also include season fixed effects because, as we later demonstrate, significant changes occur over the time period examined.

When measuring defensive unit performance, P_{it} is the number of defensive points allowed by team *i* in season *t*, and POS_{it} is a vector that includes the positional compensation terms DB_{it}, DL_{it}, and LB_{it}. When modeling offensive performance, P_{it} is the number of points scored by team *i* in season *t*, and POS_{it} includes the positional compensation terms OL_{it}, QB_{it}, RB_{it}, and TE_{it}. Each positional compensation term is the natural log of the difference between the sum of positional compensation (either base or bonus pay) for team *i* in season *t* and the average sum of compensation at corresponding positions across all teams in season *t*.[8]

When interpreting the meaning of POS_{it} variables in (3), it is important to consider the implications of the salary cap. Since the payrolls of most NFL franchises are typically near the cap limit, teams cannot appreciably increase spending on one position without reducing spending on another. However, while this is a zero-sum game, it may be the case that teams systematically under- or over-estimate the value of talent at certain roster positions. If so, then we would expect to observe significant coefficient estimates when measuring the effects of positional spending on unit performance. If there are sensitivity differences, then the intuition is that teams should

[7] We use an OLS regression when *Defensive Points Allowed* or *Offensive Points Scored* is the LHSV, and a Poisson regression when *Wins* is the LHSV.

[8] To illustrate, suppose that Team *i* spends a total of US\$ 10,000,000 on defensive backs in season *t* while the league-wide per-team average for defensive backs that season is US\$ 9,000,000. DB_{it} is calculated as ln(US\$ 10,000,000 – US\$ 9,000,000).

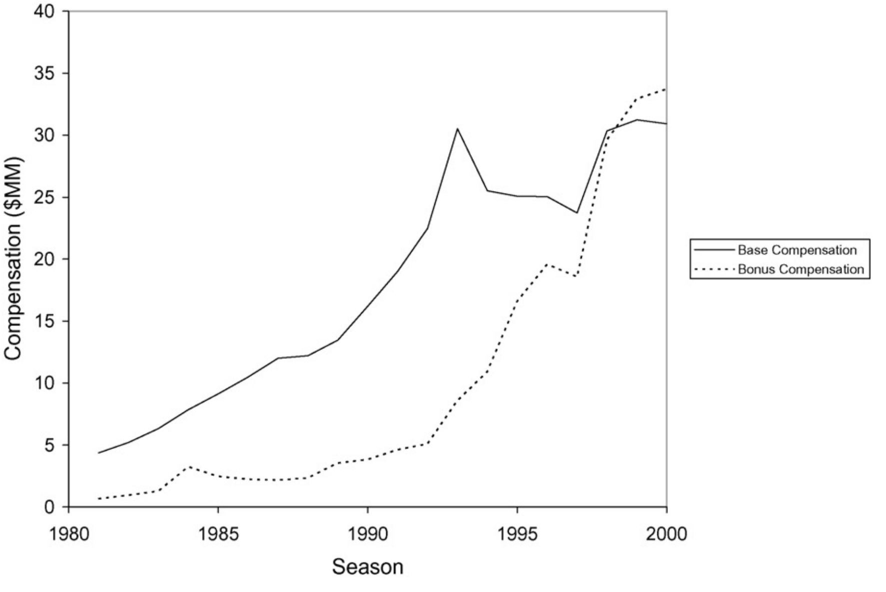

Fig. 1. Compensation trends in the NFL (1981–2000). This figure illustrates the average per-team base and bonus compensation paid by NFL franchises from 1981 to 2000, and is generated from a sample of 575 team-years.

divert resources towards (away from) positions that are more (less) significant determinants of performance.

In the final portion of our analysis, we examine the effects of variations in intra- and inter-team positional compensation (both justified and unjustified) on team wins, the optimal measure of overall organizational proficiency. We again use (3) and define performance (P_{it}) as the number of team *I*'s wins in season *t,* and terms within the vector POS_{it} consist of normalized compensation for all defensive and offensive positions. Likewise, μ, σ, and Gini are each calculated at the team level rather than at the unit level.

3. Results

We begin by illustrating the annual trends in base and bonus compensation among NFL franchises from the 1981 season through the 2000 season.[9] Fig. 1 shows that prior to the introduction of free agency in 1994, base salary represented a much greater proportion of total per-team compensation than did the bonus component. Since then, teams have presumably begun to compete more aggressively for highly talented free agents by offering larger signing bonuses.

The Lorenz curves in Figs. 2 and 3 describe the level of dispersion in base and bonus compensation across players from 1994 to 2004. To construct these figures, we pool observations by team unit—offense, defense, and special-teams. Were compensation to be perfectly evenly distributed across all players, each of these figures would be characterized by a 45° line. Instead, the plots

[9] Individual player compensation data are unavailable prior to 1994. Data for this plot are obtained from the NFLPA (NFL Players Association, 2002) and represent a different data set than that used in the remainder of the paper.

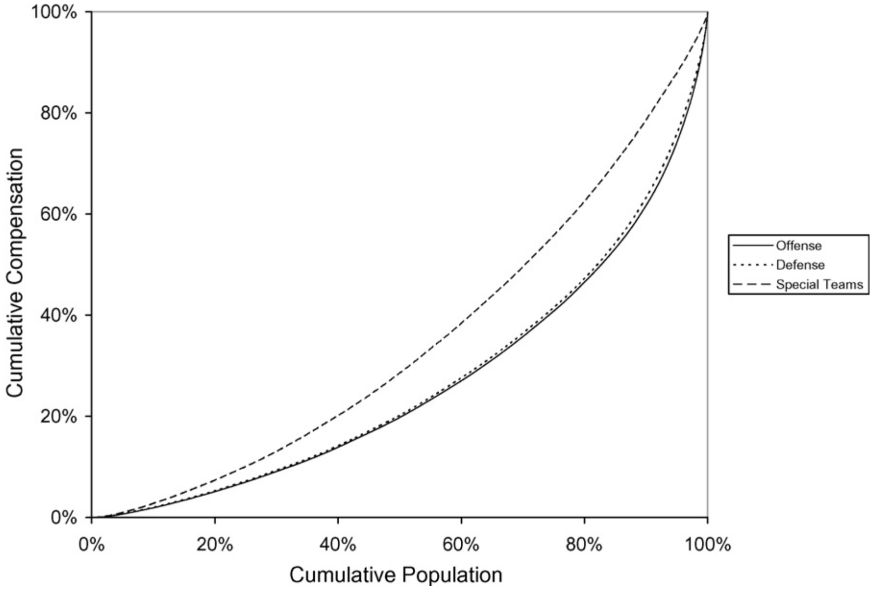

Fig. 2. NFL player base salary Lorenz curves (1994–2004). This figure illustrates the Lorenz curve of all defensive, offensive, and special-teams players in the NFL, and is generated from a sample of 19,256 player-years. The closer each plot is to a 45° line, the more equitable is the base pay distribution among players.

reveal a convex curve for each of these team units. Differences between the curves illustrated in Figs. 2 and 3 indicate that bonus pay is distributed less equally than is base pay in the CBA era.

Across the 9083 offensive player-years in our data set, the corresponding Gini coefficients for base, bonus, and total compensation are 0.42, 0.75, and 0.52 respectively. The plot of the 9410 defensive player-years results in base, bonus, and total compensation Gini coefficients of 0.43, 0.76, and 0.53 respectively. Finally, 763 special-teams (punters and kickers) player-years produce base, bonus, and total compensation Gini coefficients of 0.14, 0.48, and 0.17 respectively.

Further evidence that the compensation structure of this labor market has changed substantially since the inception of the salary cap is provided in Fig. 4, which shows league-wide base and bonus Gini coefficients each season. Bonus pay dispersion among players has increased over the past 10 years, as the league Gini has gone from 0.72 to 0.87. This pattern provides confirmation that it is appropriate to use season fixed effects in the regression models.

Fig. 5 contrasts the period examined in this study with that in Bishop, Finch, and Formby (1990). In that paper, the authors compare NFL salaries to those in Major League Baseball in 1987. At the time, MLB had a pre-existing free agency system while no such system existed in the NFL. The authors plot Lorenz curves for the NFL and MLB to show that more dispersion was present in the MLB system of free agency. Fig. 5, which illustrates just the NFL data, suggests that compensation dispersion in the NFL has increased since 1987. Whether this can be attributed to the free agency system or the introduction of a salary cap is left to future researchers.

Table 1 shows the estimates produced from specification (1), an OLS regression with player compensation (base or bonus salary) as the dependent variable. Panels A, B, and C illustrate the degree to which the proposed variables explain variations in logged injury-adjusted pay for defensive, offensive, and quarterback positions respectively. Coefficient estimates suggest that many of the proposed productivity variables are significant determinants of variations in player

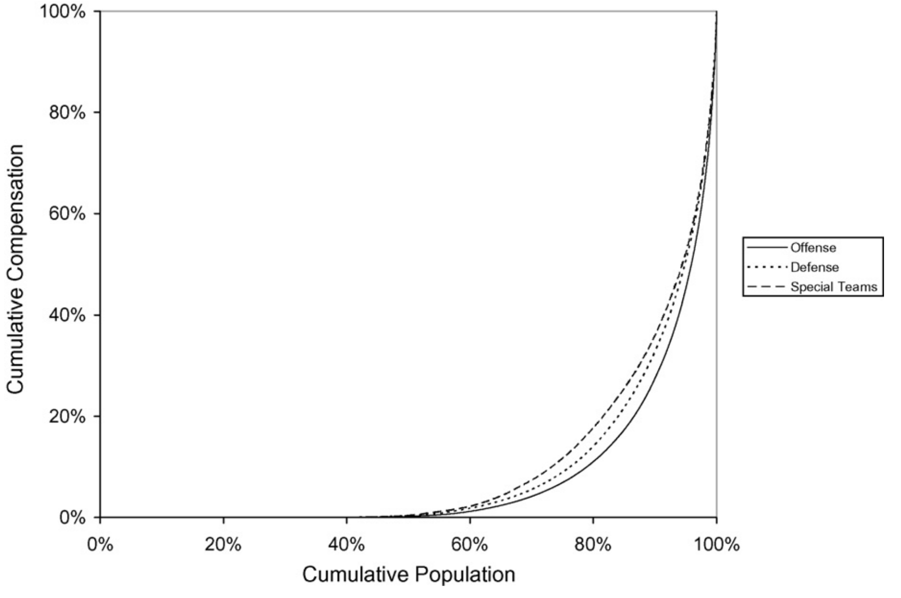

Fig. 3. NFL player bonus compensation Lorenz curves (1994–2004). This figure illustrates the Lorenz curve of all defensive, offensive, and special-teams players in the NFL, and is generated from a sample of 19,256 player-years. The closer each plot is to a 45° line, the more equitable is the bonus pay distribution among players.

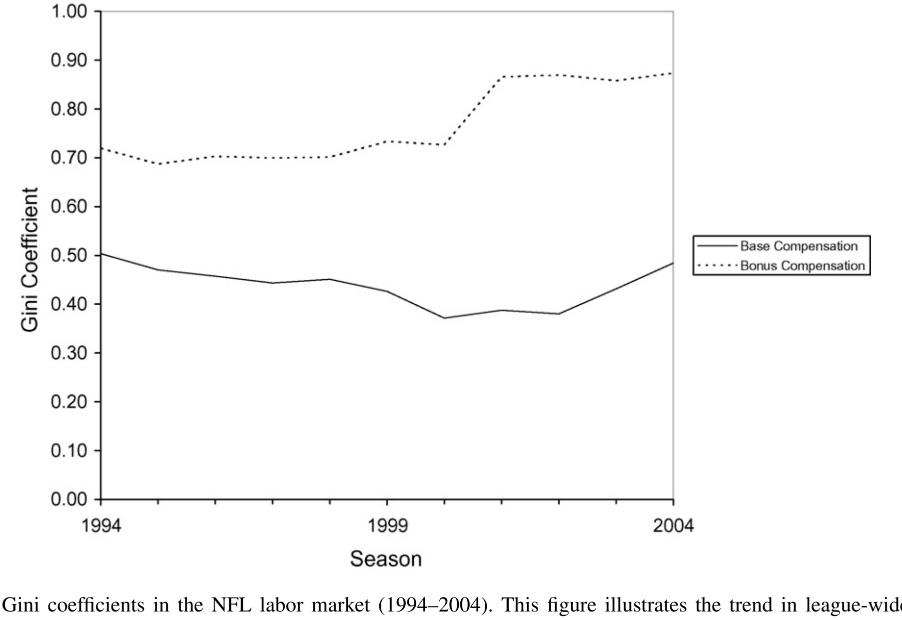

Fig. 4. Gini coefficients in the NFL labor market (1994–2004). This figure illustrates the trend in league-wide Gini coefficients over time and is generated from a sample of 19,256 player-years.

Table 1
Determinants of compensation by position

Category	Variable	Position (*N*)					
		DB (3582)		DL (3215)		LB (2613)	
		Base (0.2912[a])	Bonus (0.2751[a])	Base (0.3294[a])	Bonus (0.2847[a])	Base (0.3899[a])	Bonus (0.2790[a])
Panel A—defensive positions							
	Tackles	0.0012 (0.1932)	0.0314 (0.0000)	0.0064 (0.0000)	0.0390 (0.0000)	0.0031 (0.0001)	0.0241 (0.0000)
	Sacks	0.0276 (0.2343)	0.0335 (0.7903)	0.0197 (0.0066)	0.0595 (0.1237)	0.0328 (0.0004)	0.1894 (0.0007)
Productivity	Passes defensed	0.0218 (0.0000)	0.0985 (0.0003)	−0.0166 (0.1678)	−0.0147 (0.8185)	0.0109 (0.2973)	0.0363 (0.5635)
	Interceptions	−0.0104 (0.4574)	0.0878 (0.2457)	0.0895 (0.1405)	0.1196 (0.7120)	−0.0287 (0.2963)	0.0633 (0.7011)
	Starter	0.2083 (0.0006)	−0.0729 (0.8245)	0.0408 (0.4694)	0.6501 (0.0310)	0.0451 (0.4858)	−0.7257 (0.0622)
Draft	Round 1	0.2501 (0.0000)	0.3878 (0.1619)	0.1982 (0.0000)	1.3507 (0.0000)	0.4532 (0.0000)	1.1226 (0.0010)
	Undrafted	−0.0260 (0.4983)	−2.1372 (0.0000)	−0.1040 (0.0148)	−1.7692 (0.0000)	−0.0267 (0.4875)	−1.5014 (0.0000)
	Age < 25	−0.1644 (0.0007)	1.4913 (0.0000)	−0.1629 (0.0015)	1.9428 (0.0000)	−0.0979 (0.0490)	1.1527 (0.0001)
	Age > 30	−0.2827 (0.0000)	0.2251 (0.5381)	0.0067 (0.9208)	0.3236 (0.3719)	−0.1772 (0.0130)	−0.5096 (0.2349)
	GS	−0.0001 (0.9680)	0.0200 (0.0341)	0.0046 (0.0291)	0.0248 (0.0278)	0.0006 (0.7450)	0.0477 (0.0000)
Experience	GP	0.0158 (0.0000)	0.0067 (0.5033)	0.0160 (0.0000)	0.0168 (0.1270)	0.0200 (0.0000)	0.0013 (0.9076)
	GS^2	0.0000 (0.2151)	−0.0001 (0.3416)	0.0000 (0.4492)	−0.0001 (0.1421)	0.0000 (0.1582)	−0.0003 (0.0006)
	GP^2	−0.0001 (0.0000)	−0.0001 (0.4175)	−0.0001 (0.0000)	0.0000 (0.6001)	−0.0001 (0.0000)	0.0001 (0.1208)
	Pro Bowls	0.0413 (0.0589)	0.3179 (0.0073)	0.0777 (0.0007)	−0.0238 (0.8461)	−0.0085 (0.7021)	−0.0837 (0.5286)

Category	Variable	Position (*N*)							
		OL (3674)		RB (2007)		TE (1267)		WR (2135)	
		Base (0.3156[a])	Bonus (0.2748[a])	Base (0.2756[a])	Bonus (0.2942[a])	Base (0.2992[a])	Bonus (0.2304[a])	Base (0.3979[a])	Bonus (0.2541[a])
Panel B—offensive positions									
	Rushing Yards			0.0003 (0.0041)	0.0008 (0.0592)			0.0027 (0.0048)	−0.0058 (0.3292)
	Yards per Rush			0.0316 (0.0072)	0.0842 (0.1314)				
Productivity	Receiving Yards			0.0001 (0.6769)	0.0036 (0.0002)	0.0005 (0.0024)	0.0036 (0.0019)	0.0004 (0.0001)	0.0026 (0.0000)
	Yards per Reception					0.0133 (0.0093)	0.0334 (0.3067)	0.0096 (0.0020)	0.0636 (0.0009)
	Starter	0.4179 (0.0000)	1.8620 (0.0000)	0.1102 (0.1908)	0.1560 (0.6965)	0.0813 (0.3027)	0.7581 (0.1316)	0.1305 (0.0690)	0.3809 (0.3907)
Draft	Round 1	0.1304 (0.0086)	1.0159 (0.0001)	0.1454 (0.0557)	0.6762 (0.0610)	0.3684 (0.0000)	0.3757 (0.5107)	0.2245 (0.0000)	0.3796 (0.2653)
	Undrafted	−0.1416 (0.0001)	−1.4337 (0.0000)	−0.1533 (0.0057)	−2.3711 (0.0000)	−0.0546 (0.2904)	−2.1811 (0.0000)	−0.2228 (0.0000)	−2.0544 (0.0000)

Table 1 (*Continued*)

Category	Variable	Position (N)							
		OL (3674)		RB (2007)		TE (1267)		WR (2135)	
		Base (0.3156[a])	Bonus (0.2748[a])	Base (0.2756[a])	Bonus (0.2942[a])	Base (0.2992[a])	Bonus (0.2304[a])	Base (0.3979[a])	Bonus (0.2541[a])
Experience	Age < 25	−0.1855 (0.0000)	1.9126 (0.0000)	−0.0914 (0.1771)	1.7962 (0.0000)	−0.1715 (0.0095)	1.3944 (0.0010)	−0.2655 (0.0000)	1.2723 (0.0001)
	Age > 30	0.0480 (0.4304)	−1.0864 (0.0006)	−0.2609 (0.0153)	0.1335 (0.7937)	−0.0657 (0.4724)	0.1453 (0.8030)	−0.0218 (0.7796)	−0.2831 (0.5567)
	GS	0.0013 (0.4991)	0.0194 (0.0473)	0.0007 (0.8073)	0.0203 (0.1377)	−0.0044 (0.1559)	0.0150 (0.4477)	0.0012 (0.5751)	0.0261 (0.0552)
	GP	0.0166 (0.0000)	0.0479 (0.0000)	0.0186 (0.0000)	0.0287 (0.0147)	0.0149 (0.0000)	0.0374 (0.0090)	0.0123 (0.0000)	0.0070 (0.5936)
	GS^2	0.0000 (0.2282)	−0.0001 (0.3570)	0.0000 (0.9171)	−0.0002 (0.0757)	0.0000 (0.1821)	−0.0001 (0.6349)	0.0000 (0.2634)	−0.0001 (0.1671)
	GP^2	−0.0001 (0.0000)	−0.0002 (0.0017)	−0.0001 (0.0000)	−0.0001 (0.1811)	−0.0001 (0.0000)	−0.0002 (0.0063)	−0.0001 (0.0000)	0.0000 (0.9295)
	Pro Bowls	0.0512 (0.0071)	0.0325 (0.7434)	0.0948 (0.0110)	0.2770 (0.1176)	−0.0512 (0.1336)	0.0434 (0.8415)	−0.0179 (0.4474)	0.0516 (0.7238)

Category	Variable	N = 1116	
		Base (0.3727[a])	Bonus (0.2774[a])
Panel C—quarterbacks			
Productivity	Passing attempts	0.0000 (0.9811)	0.0286 (0.0090)
	Passing completions	0.0010 (0.7974)	−0.0269 (0.2025)
	Passing yards	0.0000 (0.9962)	−0.0010 (0.4873)
	Passing TDs	−0.0106 (0.3993)	0.0674 (0.3289)
	Interceptions thrown	0.0136 (0.2762)	−0.0425 (0.5366)
	Times sacked	0.0056 (0.2363)	0.0427 (0.0998)
	Rushing yards	0.0002 (0.6421)	−0.0026 (0.2260)
	Starter	0.2448 (0.0748)	−1.1981 (0.1133)
Draft	Round 1	0.2582 (0.0018)	0.4955 (0.2759)
	Undrafted	−0.1229 (0.0850)	−1.8746 (0.0000)
Experience	Age < 25	−0.2829 (0.0003)	1.6435 (0.0002)
	Age > 30	−0.0473 (0.6035)	−0.1995 (0.6911)
	GS	−0.0007 (0.8836)	0.0176 (0.4925)
	GP	0.0167 (0.0004)	0.0244 (0.3487)
	GS^2	0.0000 (0.8382)	−0.0002 (0.2137)
	GP^2	−0.0001 (0.0046)	0.0000 (0.7645)
	Pro Bowls	0.1599 (0.0001)	0.6289 (0.0054)

This table contains results from an OLS regression with season fixed effects. The dependent variable is base or bonus compensation. Coefficient estimates are listed along with associated *p*-Values (in parenthesis).

[a] Adjusted r^2 values.

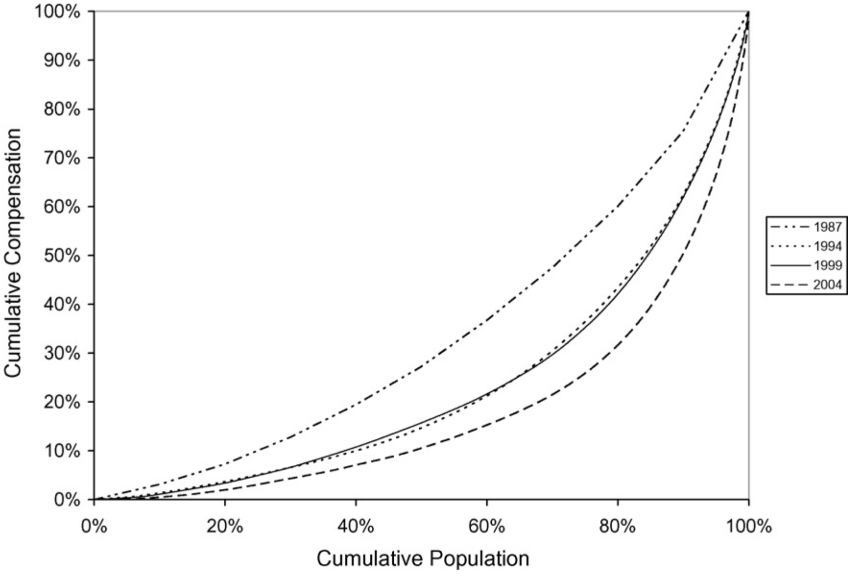

Fig. 5. Total compensation Lorenz curves in the NFL labor market. This figure illustrates the Lorenz curve for all players in the NFL before and during the salary cap era. The closer each plot is to a 45° line, the more equitable is the total pay distribution among players.

compensation, and several interesting trends appear in the draft and experience variables. For instance, even after accounting for age and game experience, players drafted in the first round earn significantly higher compensation than do others. This result is consistent with Hendricks et al. who find that compensation is based largely on *ex ante* value estimates made earlier in players' careers.

In addition, we find that younger players are more likely to receive large bonuses than are older players. Because older players typically exhibit decreasing performance levels as they age, teams may be less willing to promise them future compensation in the form of signing bonuses. Consistent with Leeds and Kowalewski, we also find that pay increases with game experience while the rate of change in compensation decreases with game experience.

The main conclusion we draw from Table 1 is that much of the variation in player compensation can be explained by readily observable factors.[10] We suggest therefore that players are, to a large degree, able to infer the amount of compensation that they and their teammates deserve, and that any differences between observed and expected pay may be perceived as unfair. Because inequity creates resentment, teams with the highest levels of unjustified spending are likely to perform worse.

To test our proposition, we examine unit-level results from (3), which measures the effects of pay allocation decisions on unit performance. We begin by studying how the distribution of resources across defensive backs, defensive linemen, and linebackers affects defensive rankings. The dependent variable in this regression is *Defensive Points Allowed*, and estimates are shown in Panel A of Table 2.

[10] When (1) is solved with total compensation (base plus bonus) as the dependent variable, positional adjusted r-squares increase to 0.6175, 0.6120, 0.6751, 0.6189, 0.6324, 0.5889, 0.6249, and 0.6758, respectively.

Table 2
Determinants of unit performance

Variable	Base	Bonus
Panel A—defensive unit performance		
Intercept	319.7904 (0.0000)	319.7329 (0.0000)
DB	−0.3218 (0.2036)	−0.4933 (0.0381)
DL	−0.1120 (0.6565)	−0.4972 (0.0317)
LB	−0.1058 (0.6767)	−0.4933 (0.0361)
Gini	−87.8488 (0.1668)	122.8916 (0.1526)
μ_S	18.9528 (0.2384)	2.8069 (0.1625)
σ_S	−3.7106 (0.7057)	1.0400 (0.6673)
μ_B	79.1318 (0.0035)	−3.8000 (0.1881)
σ_B	24.0434 (0.0106)	4.2213 (0.3428)
Injuries	0.9568 (0.0019)	0.8649 (0.0034)
Panel B—offensive unit performance		
Intercept	345.9074 (0.0000)	345.6059 (0.0000)
OL	−0.0366 (0.8977)	0.0045 (0.9863)
QB	0.5672 (0.0501)	0.5576 (0.0357)
RB	0.5639 (0.0601)	0.1542 (0.5877)
TE	0.1996 (0.5038)	0.4774 (0.1172)
WR	−0.0338 (0.9127)	0.4507 (0.1171)
Gini	−68.7484 (0.3687)	−231.5041 (0.0151)
μ_S	−19.2632 (0.1045)	−4.5408 (0.0024)
σ_S	−1.8843 (0.8171)	0.1978 (0.8943)
μ_B	−80.7481 (0.0031)	0.9024 (0.7486)
σ_B	−41.0885 (0.0003)	−4.6771 (0.2493)
Injuries	−0.4476 (0.1966)	−0.3505 (0.3115)

This table contains coefficient estimates and associated p-Values for an OLS regression with season fixed effects having specification $P_{it} = \alpha_0 + \alpha_1 \mathrm{POS}_{it} + \alpha_2 \mathrm{Gini}_{it} + \alpha_3 \mu_{\mathrm{S}it} + \alpha_4 \sigma_{\mathrm{S}it} + \alpha_5 \mu_{\mathrm{B}it} + \alpha_6 \sigma_{\mathrm{B}it} + \alpha_7 \mathrm{Injuries}_{it} + \varepsilon_i$, where P_{it} is the performance of team i as measured by total defensive points allowed in season t, Gini_{it} is the defensive unit's demeaned Gini coefficient, μ_S and μ_B are the log of demeaned unjustified compensation for defensive starters and backups respectively, σ_S and σ_B are the log of demeaned standard deviation of unjustified compensation for defensive starters and backups respectively, and Injuries is the number of player-games lost to injury by each team in each season. Coefficient estimates are shown along with associated p-Values (in parentheses).

Results from the base compensation regression indicate that teams spending more on particular positions do not perform significantly better defensively on average. This implies that organizations have been fairly efficient in allocating base pay across their defensive rosters. Were any positional coefficient to be significantly less (greater) than zero, the implication is that teams would have benefited (suffered) from paying more to acquire superior positional talent.

Moving to the base compensation dispersion terms, the insignificant coefficient estimate for Gini suggests that base salary dispersions across the defensive unit do not significantly affect performance. Thus, the presence (or absence) of highly compensated star performers is unlikely to determine defensive unit proficiency. However, the estimate for μ_B suggests that when players relegated to backup roles on a defensive unit are overpaid, unit performance drops (the positive coefficient implies that a unit characterized by relatively high μ_B allows more points to be scored against it).

Similarly, the estimate for σ_B suggests that high levels of unjustified dispersions in base pay among backups are also associated with reduced unit performance. The interpretation is that when backup players perceive that the organization allocates compensation unfairly, morale is negatively affected. Alternatively, situations in which highly paid players want, but are denied, starting roles may cause dissent among team members, a problem that is likely to be exacerbated by the local media.[11]

Estimates produced by the bonus pay regression illustrate that teams paying higher-than-league-average bonuses to defensive backs, defensive linemen, and linebackers are likely to perform better defensively. This result suggests that, during the time period examined, the marginal benefit obtained from acquiring higher talent levels at these positions exceeded the associated marginal expense.

Panel B of Table 2 illustrates the relationship between compensation and offensive points scored. Here, the correlation between base pay and performance is shown to be significant for quarterbacks and running backs (the positive coefficient estimates indicate that the unit scores more points). In addition, evidence also suggests that both unjustified base compensation and unjustified dispersion in base compensation among backups are negatively correlated with unit offensive unit proficiency.

The bonus pay regression reveals that Gini is a strong predictor of offensive unit performance, and the negative coefficient estimate suggests that teams taking a superstar-approach (those with high Gini) to personnel decisions on offense perform relatively poorly. In addition, unexplained starter bonus pay (μ_S) is negatively correlated with offensive performance, suggesting that unit morale may be damaged when some players earn pay levels that are excessive relative to their contributions. Results thus far suggest that unjustified compensation, dispersion in compensation, and dispersion in unjustified compensation vary inversely with unit performance. We next extend the same basic approach to examine overall team proficiency.

Table 3 shows the results of a Poisson regression model in which the dependent variable is the number of team wins each season. Estimates suggest that team win rates are significantly affected by player injuries. In addition, the relationship between team performance and positional spending is significant for the defensive line, quarterback, and tight end positions. Evidence also suggests that base pay levels and distributions for backups are important—teams win more games on average when unjustified pay and unjustified dispersions in pay are lower than league averages.

The negative estimate for μ_S suggests that those teams offering starters bonus pay that is most proportionate with their on-field performance are more likely to experience greater success. In other words, when franchises establish pay based on metrics other than those specified in (1), their performance is worse on average. One interpretation is that teams choosing to compensate players for intangibles such as leadership or other characteristics may be overpaying for those qualities. Alternatively, teams that take the most risks (*e.g.*, paying large bonuses to a high-profile free agents coming off career-best seasons) tend to lose on those gambles and subsequently underperform.[12]

Furthermore, the negative estimate for bonus Gini suggests that larger dispersions in bonus compensation, even if justified, are generally associated with inferior performance. This result has

[11] One example would be dissent among team members resulting from a competition between an incumbent and a high-draft-pick who is a potential replacement threat (recently, Philip Rivers vs. Drew Brees, Larry Johnson vs. Priest Holmes, and Cedric Benson vs. Thomas Jones). In each of these cases, the backup player is highly paid, team cohesion (and thus performance) may be affected by disputes over who should start, and the effect is captured by σ_B (and by μ_B if this personnel choice significantly wastes resources). This problem is not limited to high-level draft picks; many similar circumstances result from free agency acquisitions.

[12] There is recent anecdotal evidence to support this idea. For instance, the New England Patriots won three Super Bowls in four seasons by avoiding the perennial bidding wars occurring at the beginning of each season's free agency period and instead acquiring and retaining primarily mid-level free agent talent. This organization is also known for releasing star players, even fan favorites, when the asking price is perceived by ownership to be unjustifiably high.

Table 3
Determinants of team wins

Variable	Base	Bonus
DB	0.0014 (0.3543)	0.0018 (0.2270)
DL	0.0008 (0.6198)	0.0035 (0.0140)
LB	0.0001 (0.9713)	0.0006 (0.6889)
OL	0.0005 (0.7850)	0.0011 (0.4266)
QB	0.0008 (0.6324)	0.0030 (0.0422)
RB	0.0022 (0.1463)	0.0024 (0.1347)
TE	0.0043 (0.0066)	0.0006 (0.7065)
WR	−0.0012 (0.4636)	0.0002 (0.9131)
Gini	0.4937 (0.3286)	−1.8997 (0.0022)
μ_S	−0.1888 (0.1677)	−0.0547 (0.0010)
σ_S	−0.0189 (0.7757)	0.0057 (0.7906)
μ_B	−0.6345 (0.0040)	0.0199 (0.4868)
σ_B	−0.1540 (0.0205)	−0.0059 (0.8920)
Injuries	−0.0054 (0.0054)	−0.0037 (0.0574)

This table contains coefficient estimates and associated p-Values for a Poisson regression model with season fixed effects having specification $P_{it} = \alpha_0 + \alpha_1 \text{POS}_{it} + \alpha_2 \text{Gini}_{it} + \alpha_3 \mu_{Sit} + \alpha_4 \sigma_{Sit} + \alpha_5 \mu_{Bit} + \alpha_6 \sigma_{Bit} + \varepsilon_i$, where P_{it} is the number of wins of team i in season t, Gini_{it} is the team's demeaned Gini coefficient, μ_S and μ_B are the log of demeaned unjustified compensation for team starters and backups respectively, σ_S and σ_B are the log of demeaned standard deviation of unjustified compensation for team starters and backups respectively, and Injuries is the number of player-games lost to injury by each team in each season. Coefficient estimates are shown along with associated p-Values (in parentheses).

potentially important implications. Highly paid superstar players, the presence of whom increases the Gini coefficient, are overvalued because franchises do not fully account for the dissatisfaction that is likely to arise among relatively low-paid teammates.

4. Conclusions

Since the inception the salary cap prior to the 1994 season, major changes in salary structure have occurred in the NFL labor market. Guarantees have become a substantially larger component of player compensation, most likely in a response to market pressures created by free agency. In addition, the level of pay dispersion has increased, with the most talented players receiving a disproportionately large share of available wealth.

A critical issue confronting NFL franchises owners since the inception of the salary cap is how to best distribute scarce resources across their rosters. In examining the relationship between compensation and performance, we find several interesting relationships. First, evidence suggests that productivity, draft, and experience variables are significantly related to variations in base and bonus compensation. We also find evidence suggesting that team productivity is affected not only by justified and unjustified compensation levels, but also by both justified and unjustified dispersions in pay. Teams that compensate players the most inequitably are those most likely to perform the worst. An important inference is that the presence of superstar players on a roster can be disruptive, even if their productivity justifies their compensation levels.

One issue that we have not addressed is the influence that coaching ability has on maximizing player value. There is no salary cap for coaches, making it possible for teams to gain an advantage by hiring coaches who are talented at improving player performance. In addition, some head coaches and coordinators install complex offensive and defensive systems that may require several years to produce desired returns. New players in such environments provide less value to their teams in the short-term because of the learning curve associated with adapting to these systems. An important component of franchise success, then, becomes retaining and/or acquiring players that are familiar with existing systems. We leave this issue for future researchers.

Acknowledgement

We thank an anonymous referee for helpful comments and suggestions.

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