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Lancaster University Management School
Working Paper
2007/044

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Does it Pay to Specialize? The Story from the Gridiron

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Abstract:

In the field of personnel economics, there are few opportunities to convincingly test for salary returns to specialization as against versatility or multi-tasking. This paper performs such a test by modeling returns to performance measures associated with two different skills practiced by running backs in the National Football League. We find pronounced gains to specialization with substantial predicted differences in returns for alternative skills.

Moreover, these differences vary across the salary distribution. In the top half of the salary distribution, especially, model simulations show that specialists in either particular skill generate higher marginal returns than versatile players.

1. Introduction

Two of the most fundamental principles of economics, taught in ECON 101 classes worldwide, are diminishing marginal returns to labor in production and the gains, to both workers and employers, from specialization. The advantages of specialization and division of labor were highlighted in Adam Smith's celebrated example of the pin factory, with the important caveat that the extent of specialization is limited 'by the extent of the market' (Stigler, 1951). These principles seem to be well-suited to manufacturing plants with production line technology where workers perform well-defined, specific tasks. In this environment, workers generate increased productivity, and higher pay in a competitive labor market, through experience and learning by doing in their chosen specialized tasks.

In contrast to this picture of specific job tasks, a recent literature has pointed to the importance of multi-skilling and multi-task production activity in which workers are rewarded for their versatility and potential to offer synergies rather than for specialization (Black and Lynch, 2004). This literature points to the influence of Japanese firms in pioneering new human resource management policies that emphasize features of co-operation and teamwork with interchangeable processing of tasks (Carmichael and MacLeod, 1993, Baron and Kreps, 1999). One reading of the evolution of human resource management over the last 25 years is that North American and European firms imitated the 'new' human resource management policies of Japanese firms, in order to compete in increasingly global markets.

Despite the emergence of multiskilling and multitasking, professional occupations continue to be specialized. Lawyers tend to be highly specialized and production of their services is often hierarchically organized (Garicano and Hubbard, 2007). Doctors continue to specialize in particular surgical procedures and economists research in sub-fields of the

discipline. Within households, there is some evidence of significant wage premium to marriage associated with intra-household specialization in household production (Bardasi and Taylor, 2007).

Empirical identification of multi-skilling or specialization in economic activities is extremely difficult, particularly where questionnaire surveys of managers or workers are being used (Green, Machin and Wilkinson, 1998). The limitations of broad questionnaire surveys, with subjective and possibly unreliable responses, represent one good reason why some economists have recently focused on in-depth analysis of the impacts of human resource management policies in particular manufacturing plants. This approach, called ‘nano-econometrics’ from the pioneering contribution of Ichniowski and Shaw (2003) on US steel plants, allows economists to obtain precise measures of worker performance and rewards.

The present paper is an example of nano-econometrics, using the sports industry as our setting. Kahn’s (2000) description of the team sports industry as a labor market laboratory is apposite here. Each of the major North American team sports offers detailed and widely available (i.e. not proprietary) data on job tasks (positions within teams), career records, player and team performance and player salaries. In each major sport there is a plethora of on-line information tracking player performances over many years.

In American football, organized in the National Football League (henceforth, NFL), players have well-defined roles within games. Most plays are designed, at least partly, by the team’s coaches and set down in team playbooks. These designs set forth the assignment for each player on the field of play.

Although on a given play a player’s role is set, in the course of a game roles can vary. To illustrate, consider the activities of running backs. These players have three main

functions: to run with the ball (rushing), to catch passes thrown by the quarterback (pass receptions) and to block opponents to help teammates run with the ball or catch passes. The general aim of these functions is to make forward progress downfield by gaining yards in sets of four 'downs'. By making downfield progress, the team's offense aims to score points by a variety of methods, of which the most common are touchdowns, achieved by moving the ball past the opposing team's goal line, or field goals, scored by kicking the ball between the posts of the goal.

Over the history of the NFL, the best running backs have combined the rushing and pass reception functions in different ways. Barry Sanders walked away from the NFL in 1998 ending a Hall-of-Fame career. In ten years Sanders rushed for 15,269 yards, a total only eclipsed by Walter Payton and Emmitt Smith. When we consider the 2,921 yards Sanders had receiving, we see that he averaged 119 yards from scrimmage per game in his career. Per game the performance of Sander eclipsed both Payton and Smith, with Payton averaging 112 yards from scrimmage per game, while Smith only averaged 95.5 yards.

Our interest in running backs is not so much how many yards the players accumulated, but how the yards were gained. If we look at each of these backs we see that yards from scrimmage were primarily gained via rushing. For Payton, 79% of his total yards gained from scrimmage were accumulated via rushing, not catching passes out of the backfield. Sanders and Smith posted a career percentage of 84% and 85% respectively.

In contrast, Marshall Faulk proved to be a somewhat different kind of running back. In Faulk's twelve year career he gained 19,154 yards from scrimmage, a total that surpasses Sanders and rivals the career output of Smith and Payton. Relative to these other backs, though, Faulk was far less of a specialist. Only 64% of Faulk's yards from scrimmage came from rushing. While Sanders, Smith, and Payton averaged fewer than 25 yards receiving per

game, Faulk averaged close to 40 yards. In essence, Sanders, Smith, and Payton were specialists while Faulk attempted to excel at both aspects of a team's offensive attack.

The differences in how running backs gain yards motivates our inquiry. Is it better for a running back to specialize? Or does the NFL reward versatility?

The answers to these questions will be organized as follows: First, in section 2, we will examine the value of rushing and passing to a team's offensive performance. This discussion will be followed in section 3 by an empirical examination of salaries of running backs in the NFL. Do the people who are supposed to know best, the front office human resource managers in NFL franchises, pay for specialization or versatility? A concluding section 4 will summarize our findings.

2. A Balanced Attack

The first step in our analysis is to look at the impact rushing and passing has on a team's offense. Our methodology follows from the work of Berri, Schmidt, and Brook (2006) and Berri (2007).

Each of these works presented a model of offensive performance in the NFL. The dependent variable, offensive point production (OFFPTS), is the number of points a team scores that can be attributed to a team's offense.¹ This factor is then regressed on the collection of independent variables listed in Table 1a and in equation (1).

$$\text{OFFPTS} = \mathbf{a_{ik}} + \mathbf{a_1*DKO} + \mathbf{a_2*DPUNTS} + \mathbf{a_3*DFGMISS} + \mathbf{a_4*DINT} + \mathbf{a_5*DFUMLST} + \mathbf{a_6*START} + \mathbf{a_7*OFFYDS} + \mathbf{a_8*PENYDS} +$$

(+) (+) (+) (+)

¹ This is calculated by first noting that a team's offense can score via touchdowns from its rushing attack or its passing game. For each touchdown a team has the opportunity to score either one or two extra points. If a team fails to score a touchdown, a team can also score points via field goals. The NFL does not record how many extra points are derived from offensive touchdowns and how many come from touchdowns generated by a team's special teams or defense. To estimate the number of extra points from offensive touchdowns one can look at the percentage of touchdowns scored by the team's offense. One then simply assumes that this percentage represents the percentage of extra points scored by the team's offense.

$$\begin{array}{cccc}
(+ & (- & (+ & (+ \\
\mathbf{a_9*DPENYDS} + \mathbf{a_{10}*PLAYS} + \mathbf{a_{11}*3RDCON} + \mathbf{a_{12}*FGMISS} + \\
(- & (- & (+ & (- \\
\mathbf{a_{13}*INT} + \mathbf{a_{14}*FUMLST} + \mathbf{a_{15}*TDRATE} + \mathbf{a_{16}*XPCON} \\
(- & (- & (+ & (+
\end{array} \tag{1}$$

Table One separates the independent variables into four separate actions: Acquisition of the Ball, Moving the Ball, Maintaining Possession, and Scoring. Of the sixteen independent variables that comprise these actions, we are most interested in Total Offensive Yards Gained (OFFYDS). This factor, listed under Moving the Ball, is calculated by adding rushing (RUSHYDS) and passing yards (PASSYDS) together.

It is possible that rushing and passing yards have differing impacts on scoring, and before we discuss the economic returns to these actions the value of rushing and receiving on the field has to be ascertained. Consequently equation (1) was estimated with OFFYDS separated into RUSHYDS and PASSYDS. The results are reported in Table 1b.

Berri (2007) reported that each additional OFFYDS increased scoring by 0.08, or 100 additional yards would lead to 7.96 additional points. From Table Two we see that each additional RUSHYDS and PASSYDS also lead to 0.08 points. When we compare 100 RUSHYDS to 100 PASSYDS, we see that the former generates 8.30 points while the latter creates 7.85 points.

Although the coefficients on RUSHYDS and PASSYDS are virtually the same, a case can still be made for the proposition that the returns to receiving are higher than the returns to rushing. In order to acquire yards a running back must expend a Play. Table 1b indicates that each Play, holding all else constant, costs a team -0.021 points. Looking at a sample of running backs that had at least 100 rushing attempts in a season from 1994 to 2006, we can see that the average back gains 4.08 yards per rushing attempt but 7.93 yards per reception. Given these averages, to gain 100 yards rushing an average back would have

to rush 24.5 times, at a cost of 5.17 points. To gain 100 yards receiving, though, would only require 12.61 receptions at a cost of 2.66 points. When we add together the points from yards gained to the cost of the plays, we see that 100 rushing yards produce 3.13 points while 100 yards receiving generate 5.19 points. Hence, team returns to pass reception yards are greater than team returns to rush yards.

3. Economic Returns to Receiving and Running

Looking at our model of scoring it does appear that the yards a running back gains via rushing or receiving have somewhat different impacts on the field of play. Are these yards treated differently in the marketplace? To answer this question we turn to a model of player salaries.

The salary model

The model of player salaries used here follows the generic Mincer form in the sports literature where player salary is assumed to depend on experience, player performance and team characteristics (see Scully (1974) and Krautmann (1999) for baseball, Bodvarsson and Partridge (2001), Hamilton (1997) and Kahn and Shah (2005) for basketball, Berri and Simmons (2007) and Kahn (1992) for NFL, Idson and Kahane (2000) for hockey and Lucifora and Simmons (2003) for Italian soccer).

Our dependent variable is player salaries. We should note that in the NFL there are multiple measures of salary.² The basic salary is paid conditional on appearances and is not guaranteed. In addition there is often a signing bonus, which is a lump-sum payment to the player that is guaranteed and averaged over the duration of a player's contract for purposes of salary cap accounting. In addition players receive team and personal bonuses for good

performance, although we should note that these bonuses tend to be small compared to the signing bonus.

Basic salary levels are set within a pay scale determined by collective bargaining agreement between the players' association (*NFLPA*) and team owners.³ The pay scales will reflect player experience in the NFL. Signing bonuses are determined through bilateral bargaining between team owners and the player without union involvement. In any season, it follows that the variation in signing bonus will be somewhat larger than the variation in basic salary. Over our sample period, it appears that an increasing share of total player salary is accounted for by signing bonuses. For the purposes of salary cap computation, any signing bonuses are pro-rated over the life of the player's contract and the measure of salary that we will use is:

$$\text{Salary} = \text{Base salary} + \text{Pro-rated signing bonus} + \text{Other bonuses}$$

Salary distributions in most occupations are not log-normal and in team sports, skewness in the distribution is particularly marked with a few top players earning substantially more than their colleagues (Lucifora and Simmons, 2003). Non-normality and skewness in the dependent variable may result in variations of marginal returns to particular characteristics throughout the salary distribution (Leeds and Kowalewski, 2001).

We are particularly concerned with a comparison of returns to different performance measures. Since these returns are likely to vary through the salary distribution -- and as our data cover 12 NFL seasons -- we need to deflate total salary by an appropriate measure to

² Salary data is provided by *USA Today* and Rod Fort's Sports Business web site, www.rodneymfort.com/SportsData.

³ The NFL operates a salary cap which specifies an upper limit to the ratio of team payroll to gross designated revenues. The salary cap does not specify any limit on individual salaries, hence it is more accurate to refer to this as a cap on payroll. Moreover, the cap can be partly circumvented as some revenues (such as revenues from leasing luxury boxes at stadia) do not count against the cap. Nevertheless,

obtain real values. We need to do this so that a given position in the salary distribution of running backs in 1995 is similar to the same part of the distribution in 2005.

The rate of NFL salary inflation has been considerably in excess of consumer price inflation over our sample period of 1995 to 2006. Rather than deflate salaries by price inflation we scale salaries of running backs by average NFL salary in each season. The resulting values of log real salary are clearly not log-normal, as can be seen in the kernel density plot shown in Figure 1. For our sample of 1,425 player-seasons we find a kurtosis value of 3.24. Since this value exceeds 3, we have excess kurtosis and we are reluctant to proceed with ordinary least squares estimation for our model.⁴

With dependent variable described, we move on to a discussion of our independent variables. And this list of variables begins with player experience. We measure experience as the number of accumulated seasons' active performance in the NFL (*Experience*). If a player misses a season due to injury or contract hold-out this season is not counted as experience.⁵ As with the human capital model, we expect NFL experience to impact player salaries positively⁶ but with diminishing returns to reflect the wear and tear on the body and decline in physical ability (speed and strength) that is clearly apparent in playing careers that average just four years in this highly physical sport. Diminishing returns to experience are captured by a quadratic form with the addition of *Experience squared*.

the distribution of team payrolls in NFL is more compressed than in other North American sports and the salary cap can be viewed as binding.

⁴ If salaries are deflated by CPI, the kurtosis value becomes 3.84, suggesting an even stronger departure from log-normality in the dependent variable.

⁵ Player records were taken from Carroll *et al.* (1999) and various editions of the *NFL Fact and Record Book*.

⁶ In the human capital model of pay determination, workers raise their marginal revenue products through increased work experience which is associated with learning by doing. In the NFL, players do learn from on-field playing experience but the experience is itself a direct reflection of ability as team coaches will select what they regard as the best players to appear in games and particular plays. So experience in the NFL is largely a function of successful selection; and in training camps and in practice sessions, what is

NFL experience for most players – at least in our sample – is preceded by the league’s player draft. There are 12 draft rounds and players drafted in earlier rounds tend to be of higher quality than players drafted in later rounds. Hence, earlier round choices should have greater salaries. Also, players selected in earlier rounds will receive greater technical and coaching support than players selected in later rounds so the prediction that these players will earn larger salaries is partly self-fulfilling.

We should note that the draft is an imperfect predictor of playing talent, especially as teams use the draft partly as a trading exchange for players (Hendricks *et al.* 2003, Quinn (2006)).⁷ Kahn (1992) used the inverse of draft round as a control variable in models of NFL player salary to capture the non-linearity in impact of draft round number on player salary. We experimented with this specification and with a set of dummy variables for draft round and found that only rounds one and two significantly affected salary. Hence, we retain *Draft round 1* and *Draft round 2* as dummy variables to reflect draft choices. We assume that once achieved, high draft status remains an influence on player salary throughout the player’s career.

Players with three years experience in the NFL are entitled to ‘restricted free agency’. After three years, a player can seek contract offers from rival teams but the current team is entitled to present a matching offer. Such players are denoted by the dummy variable, *Restricted free agent*.

NFL players are entitled to unfettered free agency status after four seasons playing experience. Players who have at least four years experience are denoted by the dummy variable *Veteran*. Several players remained with their drafting team even though they had

classified as ‘training’ is actually an elaborate selection process designed to identify appropriate players for upcoming games.

acquired free agent status. This is presumably because the drafting team offered the player a contract with valuation at least as high as any alternative offer by another team in the market for free agents. Such players who remain with their original drafting teams despite being free agents are denoted by the dummy variable *Stayer*. This is set at one until the player switches teams. We predict that both ‘veterans’ and ‘stayers’ will earn higher salaries than players who do not have free agent status (see Krautmann *et al.* 2007 for a full account of conditions for free agency in NFL).

Inspection of our data suggests that players often receive lower salary when they change teams. We capture this effect by a dummy variable, *Change team*, where the value of unity only applies for the first season in which a player represents a different club. This variable was found to be negative and significant in the analysis of NFL quarterback salaries of Berri and Simmons (2005). Their rationale was that teams which identified an effective job match with their quarterbacks would offer salaries in excess of outside opportunities, even for free agents. Players who switch teams would then tend to be those deemed surplus to requirements. We anticipate a similar effect for running backs.

Berri and Simmons (2005) also identified appearance in the annual Pro Bowl exhibition game as an indicator of player value. In their model of NFL quarterback salaries, players who had at any time previously appeared in the Pro Bowl received higher salaries *ceteris paribus* and we expect the same result for running backs. The dummy variable for Pro Bowl appearance is denoted by *Pro bowl*.

Although characteristics unique to the players are important, we must remember that football is a team game. Specifically, this is an interactive team game with complementarity

⁷ It is common for a player to be traded in the current season in exchange for one or more draft picks of the buying team in future seasons.

between team inputs.⁸ Modeling this complementarity is still in its infancy in the sports economics literature (Borland, 2006). One promising attempt was by Idson and Kahane (2000) for the National Hockey League. They extracted measures of team-mate performance minus the performance of a given player in their data set, for the same performance variable.

Unfortunately, not all NFL players have directly observable performance metrics and this is particularly the case for players on the offensive line. These players block defensive players in an effort to give skill players the time and space necessary to move the ball. Statistics for offensive line players, though, are somewhat scarce and not independent of the numbers tracked for running backs and quarterbacks. Still, we can proxy the quality of the offensive line by noting the total salary of this unit on the team.

In a competitive labor market, offensive line payroll would be an extremely good proxy for the overall quality of the offensive line. Unfortunately, the NFL labor market is restrictive and, with just 32 teams, monopsonistic. Players who are not free agents tend to receive salaries below marginal revenue product (Krautmann *et al.* 2007) and as a result the relationship between team performance and team payrolls is expected to be weak.⁹ Consequently, the relationship between payroll and latent performance of the offensive line is bound to be imperfect. Despite the problems associated with our measure, we expect a better (more expensive) offensive line should present running backs with improved opportunities to gain yards and should hence raise their productivity and salaries. We use the log of *offensive line salary*, to include all offensive line players on a team's roster in a given season, again deflated by average NFL salary.

⁸ The same can be said of all major sports, although separation of production inputs is more apparent in baseball.

⁹ As was shown by Simmons and Forrest (2004)

Similarly, *offense salary* is the log of total salaries of all ‘skill’ players on a team’s roster minus the salary given running back in any observation, deflated by average NFL salary. By skill players, we mean quarterbacks, wide receivers, tight ends and other running backs. We predict complementarity between offensive line and running backs in team production and hence a positive coefficient on *offensive line salary*. Similar complementarity could well exist between skill players and the running back in any observation but an opposing effect may occur through the salary cap. Extra salary to other skill players takes a team closer to its cap and may necessitate a cut in salary for a given running back. Consequently, the sign of coefficient on *offense salary* will then be ambiguous.

We retain one further team characteristic which is market size. This is proxied by the log of SMSA population (*Population*). It might be argued that teams in larger markets (New York Giants and Jets) can afford to pay higher salaries than teams in smaller markets (Kansas City Chiefs and Green Bay Packers). As noted above, the NFL does have a binding salary cap that is designed to prevent this outcome. This cap is also reinforced by extensive revenue sharing of both gate and broadcast revenues. If effective, these measures should serve to reduce the impact of market size on team revenues and hence on individual pay.

We have now listed all of the individual and player characteristics we suspect impacts salary, except the specific actions running backs take on the field of play. At the onset we noted that running backs have three defined tasks: rushing, receiving, and blocking. Although most running backs focus on at least one of the first two tasks, there are some running backs – called full backs – that have blocking as their primary function. These backs typically perform relatively little ball carrying or pass receiving and are generally taller and heavier than other running backs. We create a dummy variable, *full back*, for these players.

We also examine impacts of interaction terms between *full back* and our performance measures.

Turning to our performance measures, we begin by noting that we examined the set of performance measures tracked for running backs and found that the indicator which dominated all others in predicting player salaries was yards achieved, as opposed to rushing attempts, touchdowns, or fumbles. When it comes to examining yards, we made a few distinctions. First, we predict that players with established career performance will be rewarded with higher salaries than those who lack sustained performance. Consequently, our list of performance measures begins with total career rushing yards (*Career rush yards*) and total career pass reception yards (*Career receiving yards*) up to and including two seasons before the time player salary was determined.

Although career performance is important, we also expect that what a player did most recently to matter as well. Specifically, since total salary is determined before the season in question, we expect that what transpired the previous season to be significant. Hence we include *Rush yards (t-1)* and *Receiving yards (t-1)* as our key performance metrics for running backs.

We are not simply interested in the returns to rushing and receiving. Our test for specialization of running backs uses the interaction term *Receiving yards*Rush yards*. The sign of coefficient on this term offers insight into whether or not specialization raises running back salary. If pass reception yards and rush yards are complements in salary determination we would predict the coefficient on the interaction term to be positive. This would suggest salary gains from versatility. A negative coefficient suggests that an increase in one measure of player performance reduces the marginal salary returns of the other measure. Hence, an increase in pass reception yards may reduce the marginal returns to rush yards and *vice versa*.

The implication is that running backs would be better off in salary from specialization in either pass receptions or rushing.

Our sample consists of running backs who made at least one play (rush attempt or pass reception) in the previous season, yielding 1,423 player-season observations from 624 running backs. Table 2 reports some descriptive statistics for continuous measures of salary, experience and performance. To summarize, our salary model is:

*Log salary = F(Experience, Experience squared, Draft round 1, Draft round 2, Veteran, Stayer, Restricted free agent, Change team, Offensive line salary, Offense salary, Pro Bowl, Population, Full back, Career rush yards, Career receiving yards, Rush yards, Receiving yards, Receiving yards*Rush yards)*

As with Berri and Simmons (2005), and following earlier contributions by Hamilton (1997) and Leeds and Kowalewski (2001), we adopt the quantile regression method for estimation since salaries have a non-normal distribution with substantial skewness and excess kurtosis.¹⁰ At the median, quantile regression differs from ordinary least squares in that it minimizes the sum of absolute residuals rather than the sum of squared residuals (Koenker, 2005). A strong advantage of quantile regression is that it permits estimation of marginal effects of covariates at different points of the distribution of the dependent variable. In our case, we can estimate the impacts of player performance measures on log salary at different salary quantiles. The selected quantiles for estimation are 0.1, 0.25, 0.5 (median), 0.75 and 0.9 and results are reported in Table 2a. Quantiles are estimated simultaneously and standard

¹⁰ The deflation of salaries by average NFL wage rather than by CPI now becomes pertinent. If salaries are deflated by CPI than players can move between quantiles purely by salary inflation, as opposed to sustained performance. Instead, scaling by average NFL salary in a particular season means that we can compare players at a given quantile that are several seasons apart.

errors are bootstrapped with 200 replications.¹¹ For comparison, we also show results from Huber robust or trimmed regression which is a weighted least squares estimator that adjusts the regression for the influence of outliers. Again, this method is designed to address the non-normality inherent in the dependent variable. These additional results are shown in Table 2b.

Results

The estimation of our salary model is reported in Tables 3 and 4. Although our focus is on the returns to rushing and receiving, we begin our discussion with the impact of our control variables. In Tables 3a and 3b the control variables generally have significant coefficients with signs as predicted. The median quantile regression model and the Huber regression model each deliver significant coefficients on all covariates except for *Population* and *offense salary*. The results with respect to the former indicate that there is no support for the hypothesis that teams with bigger local populations and hence market size pay higher salaries to running backs.¹²

Our discussion of the statistically significant control variables begins with experience. The turning point on *Experience* for the median regression is 6.8 years. With a typical drafting age from college of 21 or 22, this corresponds to an age level that maximizes salary of 28 or 29, a figure that is consistent with findings from other sports leagues (e.g. Lucifora and Simmons, 2003 for Italian soccer and Turner and Hakes, 2007, for Major League Baseball).

As explained previously, NFL experience is preceded by the draft. Consistent with our expectation, the impact on being picked in round 2 of the draft is generally greater than for later rounds but less than for round 1. Veteran players gain a salary premium at the

¹¹ Estimation is via the `bsqreg` command in Stata 10.0.

median above. In the bottom half of the salary distribution, there is no premium. This suggests that free agency *per se* does not raise salary; free agency must be accompanied by requisite ability.

The nature of free agency also matters. Restricted free agents earn a premium from the 0.25 quantile upward. The similarity of coefficient values of *veteran* and *restricted free agent* from median upwards suggests that franchises anticipate full free agent status of high ability players by rewarding them even after three years. Players who stay with their original team beyond free agency entitlement earn an additional premium compared to veterans who move. In fact, players who change team suffer an immediate salary reduction.

Beyond free agency, we find that players who gain Pro Bowl appearances receive increments to salary over and above performance and these are sustained for the full duration of their careers. In addition, full backs -- who tend to block rather than run with or receive the ball -- gain a salary premium as reward for their skills that are less well-observed (to the econometrician). This premium varies from 7.1 per cent at the 0.75 quantile to 11.4 per cent at the 0.1 quantile, although is insignificantly different from zero at the 0.90 quantile.

The importance of blocking is not only seen with respect to fullbacks. Specifically, at the 0.10 quantile, the coefficients of *offense salary* and *offensive line salary* are each significantly different from zero at the five per cent level. Beyond this quantile, however, only *offensive line salary* has significant coefficients. We interpret this as indicative of complementarity between the productivities of the offensive line and running backs. In essence, the quality of the offensive line blocking for a running back appears to impact his production and value.

¹² See Krautmann *et al.* (2007) for a similar result on NFL players generally.

Turning to the running back's production, we find that Career rush yards are a significant predictor of salary throughout the distribution (at 10 per cent significance or better). The significance of career receiving yards, however, is not apparent at the 0.75 and 0.90 quantiles. Below these quantiles, the impact of 100 extra career receiving yards is significantly greater than the impact of 100 extra career rushing yards.

To assess the impacts of specialization on salary, we turn to our focus variables, *Rush yards*, *Receiving yards* and *Receiving yards*Rush yards*. The coefficients on *Rush yards* and *Receiving yards* are significant and positive at all estimated quantiles. Moreover, the impacts are greater at quantiles above the median compared to below.¹³ The interaction term *Receiving yards*Rush yards* has a significant (at five per cent at least), *negative* coefficient at all estimated quantiles. Hence, the marginal salary returns to extra receiving yards declines with extra rush yards. Equivalently, the marginal salary returns to extra rushing yards declines with extra receiving yards. This is indicative of gains from specialization in either skill performed by NFL running backs.

Our results show that the marginal salary returns to one skill depend negatively on the performance level observed for the other skill. Although our results are statistically significant, it is important to also consider economic significance. Specifically, we wish to consider how the coefficients reported in Table 3a convert into predicted estimates of salary returns at different quantiles of the salary distribution.

Table 4 offers a simulation of these predicted returns, holding control variables and career rush and receiving yards constant. This permits a focus on the immediate impacts of 100 extra yards rushing or receiving. The values of rush yards and receiving yards shown in the Table are taken from the salary distribution in the neighborhood of the specified

quantile. The neighborhood is just above the preceding quintile and just below the next quantile to be estimated. Where positive, the estimated marginal returns are over and above the NFL league average salary increase for a particular season. Where negative, marginal salary returns are lower than the NFL league average, but do not necessarily imply salary reduction.

For example, consider three running backs, each at the median of the salary distribution and each with control variables (*Experience*, *Offensive line salary*, etc...). Additionally, each has the same value for career rush and receiving yards. Imagine, though, that we now observe differences with respect to *Rush yards* and *Receiving yards*. Running back A has become a rushing specialist with 900 rush yards from the previous season and zero receiving yards. His return to 100 extra rush yards is estimated as 6.47%. His return to 100 extra receiving yards is 3.83%. Running back B is now a receiving specialist with 800 pass reception yards in the previous season. His predicted marginal return to 100 extra receiving yards is 7.96%. Running back C is multi-skilled; he runs with the ball and receives passes. Suppose his previous season performance levels are 300 yards in receiving and 600 yards rushing. The predicted marginal returns to 100 extra rush yards and 100 extra receiving yards for Player C are 4.63% and 5.20%, respectively. For the multi-skilled player, therefore, there is little difference in marginal returns from extra performance in either skill, at the median. But the rewards to versatility are less than the rewards to specialization; running back C's marginal returns are dominated both by the larger returns to extra rush yards for the specialist rusher and by the larger returns to extra receiving yards for the specialist pass receiver.

¹³ Introduction of squared terms on *Rush yards* and *Receiving yards* delivered insignificant coefficients. A full translog specification of log salary is therefore inappropriate.

Moving up the salary distribution, we see greater disparities between marginal returns of the versatile players and the specialists. Consider the simulated returns at the 90th percentile in Table 4. A player that specializes in rushing with 1,700 yards rushing and zero pass reception yards gains a predicted marginal salary return of 8.36%. However, if this player has 100 extra yards pass reception and no extra rush yards, the marginal salary return is -5.03%. A receiving specialist with 1,300 pass reception yards and 200 rush yards in the previous season, derives a predicted return of 11.62% from 100 extra receiving yards but a much lower return, -6.07%, from 100 extra rush yards. A more versatile player with 700 yards rushing and 600 yards pass receptions would generate marginal returns of 1.70% from 100 extra rush yards and 6.07% from 100 extra receiving yards. At the 90th percentile, it appears from our simulation that the marginal returns to specialists from extra performance levels in the specialized skill exceed the returns to versatile players from extra performance levels in either of their key skills. Similar disparities can be derived from our simulation of estimates of log salary at the 75th percentile.

At 75th and 90th percentiles, the difference in marginal returns between specialist and versatile players has widened compared with estimates at lower quantiles. Of course, this is partly due to the fact that expected performance levels are greater at higher quantiles of the salary distribution. Consequently this makes the downward impact of our interaction term larger for a given coefficient. But the coefficients on the interaction term are also greater in absolute magnitude at 75th and 90th percentiles compared to lower quantiles. These two effects combine to deliver the disparities in marginal returns shown in Table 4.¹⁴

¹⁴ The above comparison of marginal returns held constant the accumulated career totals of players. They should be viewed as one-shot returns. Career totals respond with a lag of one season. At median and below, the returns to extra career receiving yards exceed those from extra career rush yards. This ordering reverses at 75th and 90th percentiles as returns to extra receiving yards become insignificantly different from zero. The apparent superior returns to receiving yards over rush yards in this part of the salary distribution is then

Simulations are illuminating, but let us return to the specific cases of Barry Sanders and Marshall Faulk. Both players are in our data set. As noted in the introduction, Sanders can be regarded as a running specialist while Faulk is a more versatile player. Due to the scaling of nominal salary by NFL average wage, both players appear near (actually above) the 90th percentile of the salary distribution, even though Sanders exits our sample in 1998 while Faulk first appears in our sample in 1995.

Our examination of these players will take as starting values of rush yards and receiving yards to be 1883 and 283, respectively, for Sanders (his 1995 values) and 1,381 and 1,048 for Faulk (his 2000 values). Our simulation at the 90th percentile shows returns to 100 extra yards rushing and receiving for Sanders to be 5.22% and -7.06%, respectively. In contrast, the comparable returns for Faulk are estimated as -3.27% and -1.49%. The specialist has greater returns from his particular skill of rushing compared both to the secondary skill of catching passes. Also, he generates greater returns to specialization compared to versatility. Actually, even allowing for the full impact on career values, Faulk would still have a greater pecuniary incentive to develop a specialty with respect to pass receptions rather than maintain his capability with respect to both aspects of running back performance.

In section 2, we showed that rushing yards and pass yards had virtually the same impact on a team's offensive performance. The similar impact of rushing and passing on team production is not reflected in determination of running back salaries. The two findings can be reconciled that rushing yard and receiving yard totals are achieved by a mix of players

partially offset by the delayed impact on career rush yards and then salary. The adjustment to the figures reported in Table 4 is small, however. At the 75th percentile, the impact of 100 extra rush yards on salary through career rush yards is 0.30%. At the 90th percentile the extra stimulus to salary from this source is a mere 0.46%. Hence, the additional of salary returns via career measures is rather small compared to the immediate impacts though prior season performance.

and skills; within the running back category, there is considerable heterogeneity of talent. This makes specialist activity possible within the position. Teams can employ one set of running backs as pass reception specialists and another set as rushing specialists. A third set, full backs, is used as blocking specialists.

The higher marginal returns to receiving yards over rush yards in Table 4 are consistent with the higher team returns to pass yards over rush yards that we found in section 2 above. Receiving yards have a larger impact on team outcomes and this is reflected in both marginal revenue products of running backs with respect to the two performance indicators and differentials in salary returns.

4. Conclusion

In the NFL, we observe players with well-defined tasks and precise performance measures. This facilitates an econometric investigation of salary returns to players in the ‘skill’ position of running back. We were able to test for returns to specialization by distinguishing between returns to pass reception yards and returns to running yards. For this group of players, total yards achieved in a season is found to be the most fundamental performance measure that drives player salaries.

In professional team sports, the distribution of salaries exhibits greater skewness and kurtosis than in regular occupations. The use of quantile regression helps overcome problems of non-normality of the dependent variable. This estimation method also permits a flexible empirical specification in which impacts of focus variables vary through the salary distribution.

Our analysis controls for a number of relevant covariates, including experience, draft position on entry to the NFL, free agent status and reputation proxied by appearance in a Pro Bowl. Going beyond previous studies of NFL salaries, we were able to control for team complementarity by using positional payroll as a proxy for quality of team units, in particular offensive linemen, which augment the performance and productivity of running backs. The estimated impacts of these covariates appear plausible.

Our main finding is that there are pronounced gains to specialization for running backs, particularly at the top end of the salary distribution. We find that the marginal returns to receiving (rush) yards falls with extra rush (receiving) yards. The coefficient on the interaction term between receiving yards and rush yards is negative and significant at all estimated quantiles. When we simulate the model, we find substantial predicted differences in returns from receiving and rush yards as between specialists and versatile players. Again, these differences are more pronounced at the 75th and 90th percentiles.

Having set out the case for specialization, our analysis could be usefully improved in a number of ways in future work. First, we have not explicitly modeled career duration. Running backs that specialize in pass receptions may be less prone to serious knee injuries that plague specialist rushers. A hazard analysis could complement the findings presented here although we should caution that several players in our sample have short careers of three years or less. Second, we have not fully captured variations in playing styles between teams and seasons. These variations are largely attributable to the preferences of particular head coaches. Some head coaches are more oriented towards a running game than others. Future work would usefully attempt to identify the impact of head coach strategies on utilization of running backs, their rewards and their performances.

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Figure 1

Kernel density plot of *log salary*

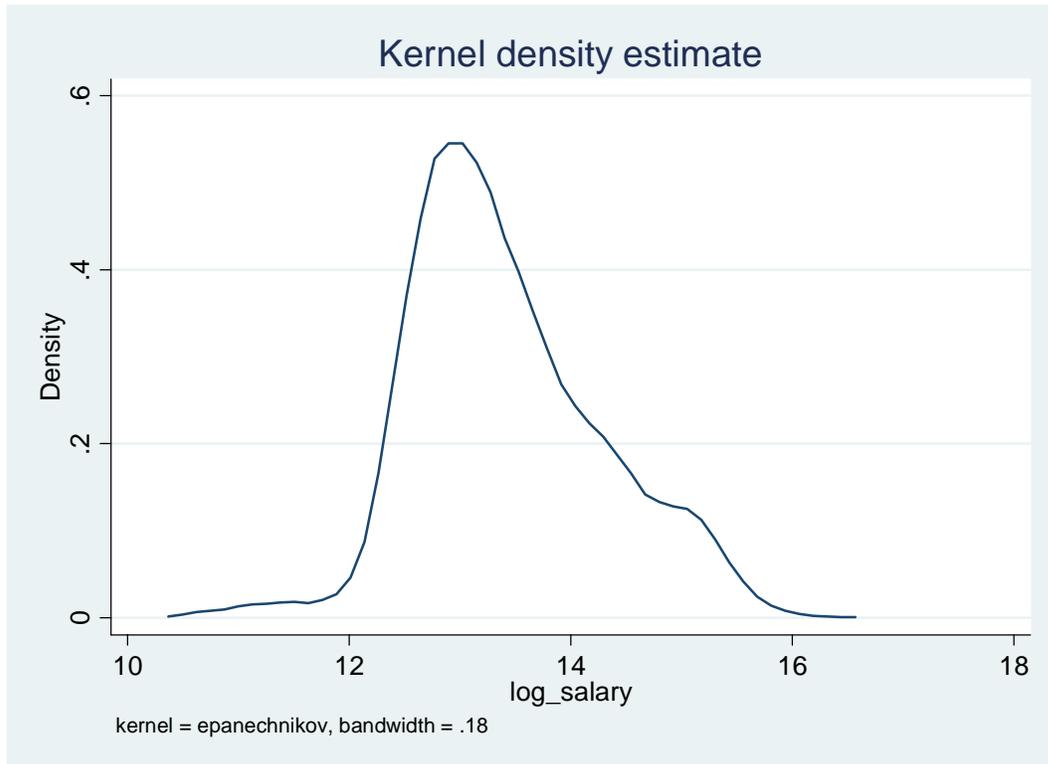


Table 1a

Factors Impacting a Team's Offensive Ability

ACTIONS	Variables Tabulated
Acquisition of the ball	Opponent's kick-offs (DKO) Opponent's punts (DPUNTS) Opponent's missed field goals (DFGMISS) Opponent's interceptions (DINT) Opponent's fumbles lost (DFUMLST)
Moving the ball	Average starting position of drives (START) Total offensive yards gained = OFFYDS = RUSHYDS + PASSYDS Total rushing yards gained (RUSHYDS) Total passing yards gained (PASSYDS) Total penalty yards lost (PENYDS) Total penalty yards lost by the opponent (DPENYDS)
Maintaining Possession	PLAYS = RUSHATT + PASSATT + SACKED Rushing attempts (RUSHATT) Passing attempts (PASSATT) Sacks (SACKED) Third down conversion rate (3RDCON) Missed field goals (FGMISS) Interceptions (INT) Fumbles lost (FUMLOST)
Scoring	Touchdown rate = TDRATE = OFFTD / (OFFTD + FGMADE) Touchdowns scored by a team's offence (OFFTD) Field goals made (FGMADE) Extra points conversion rate = XPRATE = OFFXP / OFFTD Extra points earned on offensive touchdowns (OFFXP)

Table 1b

Modeling Offensive Scoring

Dependent Variable: Offensive Points Scored (OFFPTS)

Team Fixed Effects and Dummy Variables for each season were employed.

Variable	Label	Coefficient	t-Statistic
Opponent's Kick-offs	DKO*	0.93	3.67
Opponent's Punts	DPUNTS**	0.43	2.12
Opponent's Missed Field Goals	DFGMISS	0.48	0.82
Opponent's Interceptions Thrown	DINT*	1.26	4.28
Opponent's Fumbles Lost	DFUMLST**	1.01	2.49
Average Starting Position of Drives	START*	10.03	11.17
Yards Gained, Rushing	RUSHYDS*	0.08	13.46
Yards Gained, Passing	PASSYDS*	0.08	17.98
Penalty Yards	PENYDS	-0.01	-1.21
Opponent's Penalty Yards	DPENYDS*	0.06	5.02
Plays	PLAYS*	-0.21	-4.12
Third Down Conversion Rate	3RDCON*	1.91	3.93
Field Goals Missed	FGMISS*	-3.00	-5.35
Interceptions Thrown	INT*	-1.29	-3.49
Fumbles Lost	FUMLST*	-1.49	-3.56
Percentage of Scores that are Touchdowns	TDRATE*	101.56	4.46
Extra Point Conversion Rate	XPCON	44.07	1.58
Adjusted R-squared	0.910		
Observations	251		

Note: The data utilized to estimate this model came from various issues of the *Official National Football League Record & Fact Book*. The lone exception is START, which was taken from Football Outsiders.com.

* - denotes significance at the 1% level

** - denotes significance at the 5% level

Table 2

Descriptive statistics for continuous salary, experience and performance variables

Variable	Mean	Standard deviation	Minimum	Maximum
<i>Salary</i>	1,044,211	1,288,310	52,941	15,000,000
<i>Real salary</i>	1,009,395	1,145,555	37,883	13,200,000
<i>Experience</i>	5.07	2.75	1	16
<i>Career rush yards</i>	1,259	2,259	-1	17,216
<i>Rush yards</i>	363	445	-5	2,066
<i>Career receiving yards</i>	558	925	-2	6,584
<i>Receiving yards</i>	156	171	-3	1,387

Table 3a
Quantile Regression Results

Dependent variable is log real salary for running backs with positive plays in previous season; sample period 1995-2006; N = 1423

Variable	0.10	0.25	0.50	0.75	0.90
<i>Exp</i>	0.273 (4.04)	0.214 (4.92)	0.218 (5.81)	0.163 (3.37)	0.213 (3.11)
<i>Exp squared</i>	-0.021 (4.23)	-0.016 (6.18)	-0.016 (6.40)	-0.013 (4.49)	-0.015 (3.89)
<i>Draft round 1</i>	0.559 (5.99)	0.511 (6.45)	0.596 (7.72)	0.639 (9.45)	0.697 (7.27)
<i>Draft round 2</i>	0.241 (3.17)	0.276 (5.08)	0.266 (5.88)	0.254 (5.69)	0.239 (3.03)
<i>Veteran</i>	0.105 (0.86)	0.125 (1.19)	0.168 (2.05)	0.316 (3.64)	0.299 (2.07)
<i>Stayer</i>	0.116 (1.73)	0.174 (2.98)	0.215 (4.70)	0.187 (2.91)	0.300 (3.60)
<i>Restricted free agent</i>	0.105 (1.15)	0.190 (3.21)	0.179 (3.72)	0.245 (3.81)	0.301 (3.03)
<i>Change team</i>	-0.768 (5.98)	-0.406 (6.88)	-0.277 (7.11)	-0.238 (5.32)	-0.167 (2.45)
<i>Offensive line salary</i>	0.194 (2.26)	0.178 (3.85)	0.211 (4.33)	0.172 (3.26)	0.163 (2.29)
<i>Offense salary</i>	0.181 (2.05)	0.093 (1.56)	-0.022 (0.35)	-0.063 (0.94)	-0.023 (0.23)
<i>Pro bowl</i>	0.192 (2.61)	0.236 (3.85)	0.292 (4.75)	0.435 (6.42)	0.370 (4.08)
<i>Population</i>	-0.023 (0.91)	-0.008 (0.40)	-0.005 (0.36)	-0.012 (0.67)	-0.010 (0.43)
<i>Full back</i>	0.114 (2.29)	0.104 (3.45)	0.088 (2.67)	0.071 (1.96)	-0.002 (0.03)
<i>Career rush yards</i>	0.068 (2.96)	0.032 (2.23)	0.033 (2.25)	0.030 (1.91)	0.046 (2.16)
<i>Career receiving yards</i>	0.108 (1.88)	0.129 (4.35)	0.083 (2.06)	0.056 (1.44)	0.014 (0.31)
<i>Rush yards</i>	0.0464 (5.25)	0.0595 (7.22)	0.0647 (8.19)	0.0739 (8.26)	0.0836 (6.57)
<i>Receiving yards</i>	0.0889 (5.12)	0.0646 (5.37)	0.0796 (5.17)	0.1278 (6.54)	0.1384 (4.83)
<i>Receiving yards*</i>	-0.0062 (2.44)	-0.0044 (2.06)	-0.0046 (2.02)	-0.0086 (3.65)	-0.0111(3.18)
<i>Rush yards</i>					
<i>Pseudo R²</i>	0.35	0.41	0.47	0.52	0.51

Note: t statistics are computed using bootstrapped standard errors with 200 replications. *Rush yards*, *Pass yards* and *Pass yards*Rush yards* are expressed in units of 100 yards for ease of interpretation. *Career rush yards* and *Career pass yards* are expressed in units of 1,000 yards.

Table 3b
Robust regression results

Variable	Coefficient (t statistic)
<i>Exp</i>	0.188 (5.61)
<i>Exp squared</i>	-0.014 (7.11)
<i>Draft round 1</i>	0.534 (13.09)
<i>Draft round 2</i>	0.240 (6.26)
<i>Veteran</i>	0.227 (3.18)
<i>Stayer</i>	0.210 (5.46)
<i>Restricted free agent</i>	0.231 (4.78)
<i>Change team</i>	-0.285 (9.20)
<i>Offensive line salary</i>	0.177 (4.74)
<i>Offense salary</i>	0.003 (0.07)
<i>Pro bowl</i>	0.313 (7.41)
<i>Population</i>	-0.009 (0.64)
<i>Full back</i>	0.088 (2.91)
<i>Career rush yards</i>	0.034 (3.56)
<i>Career receiving yards</i>	0.090 (3.83)
<i>Rush yards</i>	0.0679 (13.02)
<i>Receiving yards</i>	0.0891 (7.47)
<i>Receiving yards*</i>	-0.0592 (4.02)
<i>Rush yards</i>	

Table 4

Percentage returns to 100 yards extra rush yards (x) or 100 yards extra pass yards

(y): Cells denote x,y

10% quantile

$$\text{Log salary} = 0.0464 * \text{Rush yards} + 0.0889 * \text{Receiving yards} - 0.0062 * \text{Receiving yards} * \text{Rush yards}$$

		Rush yards				
Receiving yards		0	150	400	600	1300
0			4.64,7.96	4.64,6.41	4.64,5.17	4.64,0.83
100	4.02,8.89	4.02,7.96	4.02,7.96	4.02,6.41	4.02,5.17	4.02,1.79
200	3.40,8.89	3.40,7.96	3.40,7.96	3.40,6.41	3.40,5.17	3.40,1.79
300	2.78,8.89	2.78,7.96	2.78,7.96	2.78,6.41	2.78,5.17	2.78,1.79
400	2.16,8.89	2.16,7.96	2.16,7.96	2.16,6.41	2.16,5.17	2.16,1.79

25% quantile

$$\text{Log salary} = 0.0595 * \text{Rush yards} + 0.0646 * \text{Receiving yards} - 0.0044 * \text{Receiving yards} * \text{Rush yards}$$

		Rush yards				
Receiving yards		0	200	500	800	1500
0			5.95,5.58	5.95,4.26	5.95,2.94	5.95,-0.14
100	5.51,6.46	5.51,6.46	5.51,5.58	5.51,4.26	5.51,2.94	5.51,-0.14
200	5.07,6.46	5.07,6.46	5.07,5.58	5.07,4.26	5.07,2.94	5.07,-0.14
300	4.63,6.46	4.63,6.46	4.63,5.58	4.63,4.26	4.63,2.94	4.63,-0.14
600	3.31,6.46	3.31,6.46	3.31,5.58	3.31,4.26	3.31,2.94	3.31,-0.14

Median

$$\text{Log salary} = 0.0647 * \text{Rush yards} + 0.0796 * \text{Receiving yards} - 0.0046 * \text{Receiving yards} * \text{Rush yards}$$

		Rush yards				
Receiving yards		0	300	600	900	1700
0			6.47,6.58	6.47,5.20	6.47,3.82	6.47,0.14
150	5.55,7.96	5.55,7.96	5.55,6.58	5.55,5.20	5.55,3.82	5.55,0.14
300	4.63,7.96	4.63,7.96	4.63,6.58	4.63,5.20	4.63,3.82	4.63,0.14
500	3.71,7.96	3.71,7.96	3.71,6.58	3.71,5.20	3.71,3.82	3.71,0.14
800	0.49,7.96	0.49,7.96	0.49,6.58	0.49,5.20	0.49,3.82	0.49,0.14

75% quantile

$$\text{Log salary} = 0.0739 * \text{Rush yards} + 0.1278 * \text{Receiving yards} - 0.0086 * \text{Receiving yards} * \text{Rush yards}$$

Receiving yards	Rush yards				
	0	500	900	1400	1800
0		7.39,8.48	7.39,5.04	7.39, 0.74	7.39,-2.70
200	5.67,12.78	5.67,8.48	5.67,5.04	5.67,0.74	5.67,-2.70
400	3.95,12.78	3.95,8.48	3.95,5.04	3.95,0.74	3.95,-2.70
600	2.23,12.78	2.23,8.48	2.23,5.04	2.23,0.74	2.23,-2.70
1300	-3.79,12.78	-3.79,8.48	-3.79,5.04	-3.79,0.74	-3.79,-2.70

90% quantile

$$\text{Log salary} = 0.0836 * \text{Rush yards} + 0.1384 * \text{Receiving yards} - 0.0111 * \text{Receiving yards} * \text{Rush yards}$$

Receiving yards	Rush yards				
	200	700	1200	1700	2000
0	8.36,11.62	8.36,6.07	8.36,0.52	8.36,-5.03	8.36,-8.36
200	6.14,11.62	6.14,6.07	6.14,0.52	6.14,-5.03	6.14,-8.36
400	3.92,11.62	3.92,6.07	3.92,0.52	3.92,-5.03	3.92,-8.36
600	1.70, 11.62	1.70,6.07	1.70,0.52	1.70,-5.03	1.70,-8.36
1300	-6.07,11.62	-6.07,6.07	-6.07,0.52	-6.07,-5.03	-6.07,-8.36