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Determinants of Pay in the NHL

A Quantile Regression Approach

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Using data from the pre-2004-2005 lockout period, we use quantile regression to estimate the earnings function of forwards and defensemen in the National Hockey League (NHL). We find that the explanatory power of Mincer's earnings equation is smaller for low-paid players than for high-paid stars. More importantly, we find significant differences in the returns to measures of performance and other variables across the conditional earnings distribution. Our estimation results suggest that the conditional expectation model used in previous studies misses some of the subtleties of the earnings determination process in professional hockey.

Keywords: *National Hockey League; quantile regression; earnings; performance*

I. Introduction

The determination of earnings in professional sports has been examined extensively in the economics literature,[1] but there have been fewer studies on this topic with respect to the National Hockey League (NHL) than the other three major North American professional sports leagues. Most of the recent studies on salary determination in professional hockey have been concerned with the question of discrimination against Canadian Francophone players (Curme & Daugherty, 2004; Jones, Nadeau, & Walsh, 1999; Lavoie, 2000). Other studies on salary determination in professional hockey examine the relationship between violence and salary and employment in the NHL (Jones, Nadeau, & Walsh, 1997) and the impact of team effects on salaries (Idson & Kahane, 2001; Kahane, 2001). Ledley and Zygmont (2006) provide a comprehensive review of the literature on salary determination in the NHL.

Measuring the overall performance in hockey can be problematic as it relates to the joint offensive and defensive roles of players during games.[2] A player's offensive performance is easy to measure to the extent that most studies use either career points

Authors' Note: We thank Ashley Ringuette and Tim Eastman for the collection of data. We acknowledge the financial support from the Laurentian University Research Fund. We are grateful to two anonymous referees for their helpful comments. The usual disclaimer applies. Please address correspondence to Department of Economics, Laurentian University, Sudbury, Ontario P3E2C6; e-mail. cvincent@laurentian.ca.

per game (PTSGAME) or goals and assists per game. His defensive performance, however, is inherently more difficult to measure. Statistics such as a player's career plus–minus record (PLUSMINUS), his career penalty minutes per game (PIMGAME), and his height (HEIGHT) or weight (WEIGHT) have been used to capture some of the player's defensive skills. These statistics, however, may be poor proxies for defensive performance and to some extent they also measure a player's offensive skills not captured by points per game. To the extent that these proxies are indeed poor measures of defensive performance and if defensive and offensive ability are related, estimates of the returns to offensive performance in the earnings equations will be biased.

The difficulty in estimating an earnings function for hockey players is further complicated because most studies on salary determination in the NHL use the standard conditional expectation model to estimate earnings equations. The focus on the conditional mean may misrepresent the relationship between earnings and performance if there are differences in the returns to performance along the conditional distribution. For example, consider the returns to penalty minutes, a proxy for a player's aggressiveness. Are the returns to additional penalty minutes identical for low-paid ''grinders'' and high-paid ''stars''?[3] The standard conditional expectation model assumes that the relationship between players' earnings and penalty minutes is the same for both types of players. However, they are typically at different ends of the earnings distribution. An empirical finding that the return to penalty minutes is insignificant at the conditional mean may be the result of offsetting significant positive returns for the low-paid grinders and significant negative returns for the high-paid stars. Alternatively, a finding that the returns to penalty minutes are positive and significant at the conditional mean may reveal the existence of significant positive returns for players only in the middle of the conditional distribution while there are insignificant returns at the tails of the distribution. In another example, consider the distinction between defensive and offensive forwards. Purely offensive forwards score goals; purely defensive forwards prevent goals. It is not unreasonable to expect the returns to scoring to be different for these two types of players who may or may not be at different points of the conditional earnings distribution. The focus on the conditional expectation model precludes any investigation of how the returns to performance may vary along the earnings distribution.

In this article, we use quantile regression to gain additional insight into the offensive–defensive dichotomy. By estimating earnings equations at different points of the conditional distribution, we can estimate the returns to the performance variables of high-paid stars and compare them with low-paid grinders. We can also investigate the questions posed earlier about the returns to career penalty minutes.

Although quantile regression has been used extensively in labor economics, educational economics, and the analysis of economic growth, we know of only two other studies in sports economics that estimate earnings equations using quantile regression.[4] Leeds and Kowalewski (2001) show that the relationship between pay and performance became stronger for low-paid players compared to high-paid players after the 1993 collective bargaining agreement between the National Football League and the National Football League Players Association. In the other study, Hamilton (1997) shows that in the mid-1990s, White players in the National Basketball Association (NBA) received a significant premium over Black players only at the upper end of the earnings distribution.

In our quantile regression model, we specify a parsimonious earnings equation that includes as explanatory variables those variables that are commonly used in the literature. Using earnings data from the 2003-2004 NHL season and career statistics up to this year, we estimate separate earnings equations for forwards and defensemen at the 10th, 25th, 50th, 75th, and 90th quantiles of the conditional earnings distribution. For each position, we compare the estimated returns to performance and other variables across the quantiles with those from the conditional mean estimated using ordinary least squares (OLS).

The rest of the article is organized as follows. Section II presents the methodology, followed by the empirical specification of the earnings equation and the description of the data. Section III presents the estimation results for forwards and defensemen. Finally, some concluding remarks are drawn in the final section.

II. Methodology and Empirical Specification

A. The Model

The standard approach to modeling earnings specifies a log-linear earnings equation that includes, as explanatory variables, measures of offensive and defensive performance, experience, reputation, and franchise characteristics. Let SAL_i denote player i's earnings, LNSAL_i the natural logarithm of earnings and x_i a vector of explanatory variables. We assume that the conditional mean of the dependent variable LNSAL is a linear function of the explanatory variables x:

$$\mathrm{LNSAL}_i = \alpha + \beta x_i + u_i \text{ and } E(\mathrm{LNSAL}_i|x) = \alpha + \beta x_i, \tag{1}$$

where α is the constant term, β is a vector of unknown parameters, u_i is an unknown error term that satisfies the classical distributional assumptions, and $E(\mathrm{LNSAL}|x)$ is the conditional mean of LNSAL. Estimates of the parameters in β are obtained using OLS.

In the standard approach, the focus is on explaining earnings at the conditional mean and we assume that the marginal effect of an explanatory variable does not change along the conditional earnings distribution. In contrast, the quantile regression model introduced by Koenker and Bassett (1978) is less restrictive in modeling earnings in the sense that the marginal effect of an explanatory variable is allowed to vary at different points of the conditional distribution. The quantile regression model specifies that the θth quantile of the conditional distribution of LNSAL is a linear function of the explanatory variables x:

$$\mathrm{LNSAL}_i = \alpha(\theta) + \beta(\theta)x_i + \nu_{\theta i} \text{ and } Q^{\theta}(\mathrm{LNSAL}_i|\, x_i) = \alpha(\theta) + \beta(\theta)x_i, \quad 0 < \theta < 1 \quad (2)$$

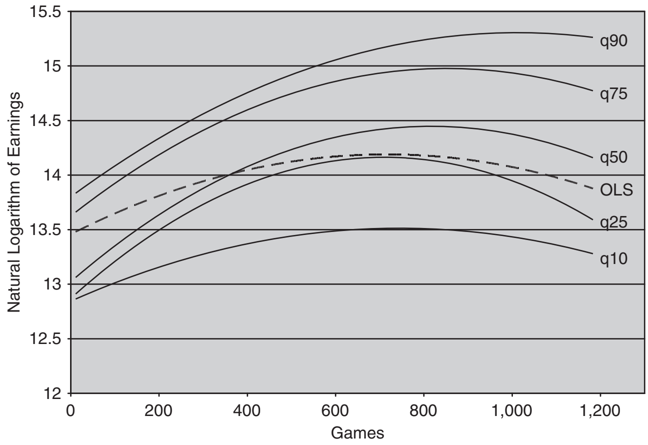
where $\alpha(\theta)$ is the constant term, $\beta(\theta)$ is a vector of unknown parameters, $\nu_{\theta i}$ is the unknown error term, and $Q^{\theta}(\mathrm{LNSAL}_i|x_i)$ is the conditional quantile function. No distributional assumptions are made about the error term $\nu_{\theta i}$ other than that it satisfies the constraint $Q^{\theta}\,(\nu_{\theta i}|x_i) = 0$. Because the vector of parameters $\beta(\theta)$ depends on the quantile θ, the marginal effect of any explanatory variable on LNSAL varies along the conditional distribution. The parameters in $\beta(\theta)$ can be interpreted in a manner similar to those of the conditional expectation model. For example, the parameter on, say, points per game at the 25th quantile ($\theta = 0.25$) gives the change in LNSAL resulting from a change in points per game for players in the bottom quarter of the conditional distribution of LNSAL.

The estimation of the quantile regression model is detailed in the methodological survey of Buchinsky (1998). The quantile regression estimates of $\beta(\theta)$ for a given quantile θ, $0 < \theta < 1$, are obtained by solving the problem:

$$\min_{\hat{\beta}_\theta} \left\{ \sum_{i:\mathrm{LNSAL} \geq x_i\beta(\theta)} \theta|\mathrm{LNSAL} - (\alpha(\theta) + \beta(\theta)x_i)| + . \atop \sum_{i:\mathrm{LNSAL} \leq x_i\beta(\theta)} (1-\theta)|\mathrm{LNSAL} - (\alpha(\theta) + \beta(\theta)x_i)| \right\} \quad (3)$$

This minimization problem does not have an explicit form solution but the estimates of $\beta(\theta)$ can be obtained by linear programming methods. It can be shown that the estimator is asymptotically normally distributed; therefore, Wald tests involving joint and individual restrictions on the parameters at the θth quantile are easy to set up. We can also test for the equality of the slope parameters across quantiles. For example, we can test for the equivalence of the slope parameter of an individual explanatory variable at the θ_ith quantile against the same slope parameter at the θ_jth quantile. Furthermore, we can do a joint test on all the slope parameters at the θ_ith quantile with those at the θ_jth quantile. More generally, we can confirm whether or not the earnings equation described by the quantile regression is better than the one under OLS. If we reject the null hypothesis that the vector of parameters $\beta(\theta)$ in equation (2) does not change with θ, OLS can be rejected in favor of quantile regression. If, however, we cannot reject the null hypothesis of equivalence of the slope parameters across the quantiles, the quantile regression model reduces to the standard conditional expectation model with identical slope coefficients and different intercept terms across the quantiles. For example, we would not reject the null hypothesis of equivalency if the data are homoskedastic.

Figure 1
Estimated Relationship Between Earnings and Games for Defensemen Under OLS and Quantile Regression



Note: OLS = ordinary least squares.

A graphical representation of the typical results of a quantile regression helps to set ideas. Figure 1 illustrates the previous discussion of the different marginal effects of variables across quantiles. It shows the earnings of NHL defensemen at various quantiles of the log of the salary distribution when all other continuous variables are evaluated at their means and dichotomous variables are set to zero. The average number of games is approximately 400. Comparing the slopes of the curves at this average level, the marginal effect of experience (as measured by games) is different from OLS at all quantiles. Moreover, at other levels of experience, the marginal effects are noticeably different across quantiles.

B. Empirical Specification

The explanatory variables and their expected signs are listed in Table 1. Intangible skills associated with experience are expected to yield positive returns and are captured by the number of games played over the career in the NHL (GAMES). Any nonlinearity effect of experience on earnings is captured by its square (SQGAMES). The positive relationship between earnings and offensive performance is primarily measured by PTSGAME. The other performance measures include the player's PIMGAME and his career plus–minus record per game (PLUSGAME). Penalty minutes per game are used to capture a player's aggressiveness and his intensity of play.

Table 1
Description of Variables

Variable	Description	Expected Sign
LNSAL	The natural log of player salary	+
PTSGAME	Career points per game	+
GAMES	Career games appeared	−
SQGAMES	The square of GAMES	+
STAR	Dichotomous variable equal to one if the player was nominated to the first or second All-Star teams and equal to zero otherwise	+
DRAFT	Dichotomous variable equal to one if the player was drafted in the first two rounds of the entry draft and equal to zero otherwise	+
TEAMREVENUE	Team revenue	+
PIMGAME	Career penalty minutes per game	+
PLUSGAME	Career plus–minus per game	+
WEIGHT	The weight of the player in pounds	+
HEIGHT	The height of the player in inches.	+
QMJHL	Dichotomous variable equal to one if the player played his junior career mainly in the QMJHL and equal to zero otherwise	?
WHL	Dichotomous variable equal to one if the player played his junior career mainly in the WHL and equal to zero otherwise	?
USCOLLEGE	Dichotomous variable equal to one if the player played mainly in the college system during his amateur years and equal to zero otherwise	?
EUROPE	Dichotomous variable equal to one if the player played mainly in European leagues during his amateur years and equal to zero otherwise	?

The plus–minus statistic is a measure of a player's two-way play: it is the difference between the number of times the player is on the ice when his team scores a goal and the number of times he is on the ice when an opposing team scores a goal. In both cases, the teams are at even strength. We expect a positive relationship between earnings and these two variables.

Physically, larger players may be able to use their size to gain an advantage during games by obstructing the play of opposing players and by creating scoring opportunities for themselves and teammates. In this case, we also include the HEIGHT and WEIGHT of players in the earnings equations. We expect a positive relationship between earnings and the size of the player.

The reputation of a player is also expected to yield additional positive salary returns that are not captured by the offensive and defensive performance measures as fans are attracted to the player's star power. Reputation in our model is captured by the dichotomous variable STAR that indicates whether or not a player was ever selected to either a first or second All-Star team during his career.

The variable DRAFT indicates whether or not the player was selected in the first two rounds of the NHL Entry Draft. A player who is selected in the early rounds of the draft may be able to negotiate a higher salary in his initial contract, especially if his initial skills are a good indicator of future performance that may persist throughout his career.

We also control for differences in the capacity of teams to compensate players by including the total revenues of the team (REVENUE) in the model. We expect a positive relationship between revenues and earnings.[5]

Unlike most studies in the literature, we control for a player's amateur background. We do this by including dichotomous variables that indicate if a player played most of his junior hockey in the Ontario Hockey League (OHL), the Quebec Major Hockey League (QMJHL), the Western Hockey League (WHL), the university or college system in the United States or Canada (USCOLLEGE), or in Europe (EUROPE). Jones et al. (1999) argue that the university- or college-trained players and the European players may experience higher opportunity costs and could therefore demand higher initial salaries. Junior hockey variables can also be used as proxies for a player's style of play. In a model that predicts a player's offensive performance in the NHL based on his position (forward or defense), his ranking in the entry draft, and the year in which he was drafted, Dawson and Magee (2000) find that the European players exceeded their predicted performance in a model that treats them the same as North American players. The authors suggest that the better-than-expected performance of European players, in terms of career total NHL season points, may result from a tendency of North American players to be more defensively minded. Voyer and Wright (1998) also examine the factors that predict the performance of NHL players. They find that offensive performance in junior hockey (goals or points per game scored) was the only significant predictor of NHL performance for many European players. The offensive performance, measured similarly, of Canadian and American born players in junior hockey was also the major predictor of their performance in the professional league. However, for them, penalty minutes, weight, and reputation were also significant predictors, but with smaller effects. Amateur background may also represent unmeasurable forces related to networking possibilities. If Ontario-based agents dominate the NHL, this could provide OHL players with a comparative advantage in salary negotiations.[6]

C. The Data

Our data set contains career information on 625 players: 407 forwards and 218 defensemen. Players are included if they played at least 10 games in the NHL and

Table 2
Summary Statistics by Position

	All Players	Forwards	Defensemen
Salary (US$)	1,847,006	1,899,211	1,749,541
LNSAL	14.04	14.05	14.04
GAMES	405.33	410.63	395.40
PTSGAME	0.394	0.467	0.257
PIMGAME	0.897	0.833	1.018
PLUSGAME	–0.010	–0.012	–0.011
HEIGHT (inches)	73.33	72.78	74.04
WEIGHT (pounds)	204.84	201.35	211.38
TEAM REVENUE (millions US$)	70.29	70.16	70.55
STAR	0.063	0.072	0.050
DRAFT	0.476	0.476	0.477
OHL	0.206	0.221	0.179
QMJHL	0.093	0.100	0.078
WHL	0.192	0.165	0.243
USCOLLEGE	0.218	0.229	0.198
EUROPE	0.291	0.286	0.303

salary data for the 2003-2004 season are available.[7] The reported earnings of players were obtained from the NHLPA Web site. Data on the performance of players, including total points, penalty minutes, and PLUSMINUS refer to their regular season career statistics prior to the 2003-2004 season. The players' performance data and physical characteristics were obtained from the NHL Official Guide and Record Book (2004). Most players in our sample played their entire junior (amateur) hockey in only one of the three major junior hockey leagues in Canada, in Europe, or in the U.S. college system. A relatively small number of players played their amateur hockey in more than one system. These players were assigned to the junior system in which they last played before joining the professional ranks.

Table 2 reports summary statistics by player position. On average, players in both positions have similar earnings but the dispersion of salary is greater in the case of forwards. Forwards average 15 more games of experience than defensemen and they score 81% more points per game. However, defensemen are 10 pounds heavier, are slightly taller, and they spend more time in the penalty box than forwards. Only 5% of defensemen have been named to the first or second all-star teams compared to 7% of forwards. Almost half of all players in both positions were drafted in the first two rounds of the draft. Approximately 30% of the forwards and defensemen are European based. Players from the QMJHL represent 10% of forwards and less than 8% of the defensemen in our sample. The remaining forwards are almost equally distributed across the remaining three amateur systems while more defensemen come from the WHL.

III. Estimation Results

A. Forwards

The OLS estimates for forwards are presented in the first column of Table 3. The results are similar to those found in the literature. Experience (GAMES, SQGAMES), PTSGAME, a selection to an All-Star team (STAR), being drafted in the first two rounds of the entry draft (DRAFT), and intensity of play and aggressiveness (PIMGAME) have the expected positive signs and are significant at the 5% level. A player's PLUSMINUS, team revenues (REVENUE), and the junior league variables (QMJHL, WHL, USCOLLEGE, and EUROPE) have insignificant coefficients. A player's HEIGHT is not significant but his WEIGHT has a negative sign and is significant at the 10% level. It seems that controlling for height, heavier forwards may not be as productive and therefore earn less, although the magnitude of the effect on earnings is fairly small.

Quantile regression permits more thorough analyses. The results of the quantile regressions are presented in Table 3 for the five quantiles ($\theta = 0.10, 0.25, 0.50, 0.75, 0.90$).[8] The table also presents goodness of fit measures in the last row. The traditional model explains less variation in the earnings of low-paid forwards than of high-paid stars. The estimates of the pseudo-R^2 for the quantile regressions show that the earnings equation explains 32% of the variation at the 10th quantile and the explanatory power increases steadily across the conditional distribution to 62% at the 75th and 90th quantiles.

Experience (GAMES, SQGAMES), PTSGAME, STAR, and DRAFT also have positive and significant effects on salary at all quantiles at the 5% level. At the same time, the HEIGHT of a forward, his PLUSMINUS, and REVENUE are not significant at any quantile. A player's WEIGHT has a negative and marginally significant impact at the median only. Although none of the junior league variables were significant under OLS, the quantile regressions show that forwards from the Quebec Major Junior Hockey League at the 75th quantile and forwards from the college system at the 50th quantile earn less than forwards from the OHL but the effect in both cases is only marginally significant at the 10% level.

The quantile regressions also show that the relationship between penalty minutes and earnings is much more complex than the one suggested by OLS. Although a player's intensity of play and aggressiveness (as measured by PIMGAME) is significant under OLS, the quantile regressions show that penalty minutes are significant only for those players in the top half of the conditional distribution. There is no significant relationship between minutes spent in the penalty box and earnings at the lower 10th and 25th quantiles. The positive relationship between the two variables is significant at the median, the 75th and 90th quantiles. Teams reward time spent in the penalty box for some players but low-paid grinders are not rewarded for putting their team at a numerical disadvantage. Perhaps, penalty

Table 3
Quantile and OLS Estimates for Forwards ($n = 417$)

	Regression Coefficients					
Variable	OLS	Q10	Q25	Q50	Q75	Q90
GAMES	9.15E-04*** (0.000)	5.79E-04*** (.020)	9.64E-04*** (.000)	8.63E-04*** (.000)	9.88E-04***(.000)	9.49E-04*** (.000)
SQGAMES	–1.43E-06***(.000)	–1.88E-06*** (.002)	–1.47E-06*** (.000)	–1.25E-06*** (.000)	–1.35E-06*** (.000)	–1.92E-06*** (.000)
PTSGAME	2.018*** (.000)	1.484*** (.000)	1.854*** (.000)	2.173*** (.000)	2.187*** (.000)	2.204*** (.000)
PIMGAME	0.096*** (.006)	0.054 (.452)	0.049 (.418)	0.115*** (.005)	0.087*** (.007)	0.075** (.079)
PLUSGAME	0.281 (.126)	0.558 (.121)	0.144 (.673)	0.170 (.446)	0.244 (.183)	0.386 (.111)
HEIGHT	0.024 (.152)	0.009 (.807)	0.022 (.349)	0.023 (.208)	0.008 (.605)	0.025 (.299)
WEIGHT	–0.004** (.081)	–0.002 (.619)	–0.003 (.243)	–0.005** (.100)	–0.001 (.709)	–0.003 (.297)
REVENUE	4.69E-05 (.973)	–2.31E-03 (.370)	–1.66E-03 (.436)	3.22E-04 (.842)	4.71E-04 (.724)	–6.02E-04 (.736)
DRAFT	0.256*** (.000)	0.355*** (.001)	0.270*** (.000)	0.219*** (.000)	0.213*** (.000)	0.241*** (.000)
STAR	0.330*** (.007)	0.710*** (.020)	0.533*** (.011)	0.307** (.034)	0.216** (.070)	0.337*** (.017)
QMJHL	–0.066 (.493)	–0.153 (.556)	–0.015 (.907)	–0.060 (.491)	–0.134 (.101)	–0.154 (.339)
WHL	–0.032 (.627)	0.125 (.508)	–0.032 (.734)	–0.086 (.218)	–0.122 (.121)	–0.125 (.176)
USCOLLEGE	0.001 (.992)	–0.106 (.492)	–0.169 (.110)	–0.126 (.106)	–0.036 (.681)	0.081 (.428)
EUROPE	0.043 (.493)	0.046 (.765)	0.005 (.953)	–0.041 (.534)	–0.084 (.270)	–0.072 (.473)
CONSTANT	14.044*** (.000)	13.510*** (.000)	13.847*** (.000)	14.131*** (.000)	14.385*** (.000)	14.523*** (.000)
R^2 (pseudo)	0.758	0.324	0.473	0.572	0.623	0.618

Note: Each continuous variable is measured in deviations from its mean. The p values for OLS are based on White heteroskedastic standard errors. The p values for the quantile regressions are derived standard errors computed from 3,599 bootstraps. Two-sided p values are in parenthesis. OLS = ordinary least squares.
**Significant at 5% for one-sided t test.
*** Significant at 1% for one-sided t test.

minutes is capturing two separate effects. The low-paid players may be incurring retaliatory penalties unassociated with attempts to score. These could be categorized as unproductive penalties. High-paid players may be incurring penalties while aggressively forechecking and displaying more intensity in attempting to gain control of the puck and/or score goals.

The marginal effects of the explanatory variables across quantiles yield interesting results. Because the dependent variable is the natural logarithm of earnings, the slope estimates represent percentage changes in earnings. However, similar percentage changes in earnings across the quantiles translate into greater changes in the level of earnings at the upper quantiles of the distribution. In addition, larger percentage changes at the lower quantiles may not translate into greater changes in the level of earnings than lower percentage changes at the higher quantiles. Therefore, it is instructive to examine the marginal effects of the explanatory variables on the level of earnings across the quantiles instead of comparing the percentage changes.

From the monotonic equivalence property of quantile regression models, the exponential transformation of $Q^{\theta}(\text{LNSAL}_i|x_i)$ leads to the fitted conditional quantile on the level of earnings. For continuous explanatory variables that are measured in deviations from their means, we have

$$\hat{Q}^{\theta}(\text{SAL}|x) = e^{\hat{\alpha}^{(\theta)} + \sum \hat{\beta}_x(\theta)(x-\bar{x})}. \tag{4}$$

If the explanatory variables are evaluated at their means, the marginal effect of a continuous explanatory variable on the level of earnings is given by

$$\partial\hat{Q}^{\theta}(\text{SAL}|x)/\partial x_i = \hat{\beta}_{x_i}^{(\theta)} e^{\hat{\alpha}^{(\theta)}}. \tag{5}$$

For a dichotomous variable, its impact on the level of earnings is measured by

$$\hat{Q}^{\theta}(\text{SAL}|x, D_i = 1) - \hat{Q}^{\theta}(\text{SAL}|x, D_i = 0) = e^{\hat{\alpha}^{(\theta)}}\left(e^{\hat{\beta}_i} - 1\right). \tag{6}$$

In the case of the standard conditional expectation model, the expected value of earnings is

$$E(\text{SAL}|x) = e^{\hat{\alpha} + \sum \hat{\beta}_x(x-\bar{x}) + u} = e^{\hat{\alpha} + \sum \hat{\beta}_x(x-\bar{x})} E(e^u). \tag{7}$$

If the error term u_i is normally distributed, $N \sim \left(0, \sigma_u^2\right)$, a consistent estimate of expected earnings is given by

$$\widehat{\text{SAL}} = \exp\left(\text{LNSAL} + 0.5\hat{\sigma}^2\right). \tag{8}$$

where $\hat{\sigma}^2$ is the unbiased estimator ofσ_u^2.[9] The marginal effect of an explanatory variable on the level of earnings measured is given by

$$\partial\widehat{\text{SAL}}/\partial x_i = \beta_i \exp(0.5\hat{\sigma}^2)\exp(\widehat{\text{LNSAL}}). \tag{9}$$

If the explanatory variables are measured in deviations from their means, the marginal effect of x_i at the means is

$$\partial\widehat{\mathrm{SAL}}/\partial x_i = \beta_i \exp(0.5\hat{\sigma}^2)\exp(\hat{\alpha}). \quad (10)$$

Table 4 presents the effects of the explanatory variables on the level of earnings when all continuous independent variables are evaluated at their means and the dichotomous variables are evaluated at zero.[10] In this case, career penalty minutes, the player's weight, and whether or not the player's junior roots are in the Quebec Major Junior Hockey League or college system are significant only at some quantiles. In the case of PIMGAME, the approximate returns of 11% and 9% and 8% at the median, the 75th quantile, and the 90th quantile translate to increases in earnings that vary from US$157,578 to US$151,287. Under OLS, the estimated effect of penalty minutes on the level of earnings is much lower at US$132,904. Regarding the junior league variables, forwards who played their junior hockey in the QMJHL earn approximately US$221,000 less than forwards from the OHL at the 75th quantile, while forwards from the college system earn approximately US$163,000 less at the median.

The other explanatory variables are significant at all quantiles. In the case of PTSGAME, the marginal impact increases as we move from the lower tail of the conditional earnings distribution to the upper tail. Ceteris paribus, the marginal effect of points per game increases from US$1.10 million at the 10th quantile to US$2.97 million at the median and US$4.47 million at the 90th quantile. This subtle but important variability is unobservable under OLS where the more simplistic result at the mean is an effect of US$2.8 million. Being selected in the first two rounds of the draft has a smaller effect on earnings at the 10th quantile (US$313,972) than for high-paid players at the 90th quantile (US$553,785). However, STAR is worth more to low-paid players and high-paid stars than players in the middle of the conditional earnings distribution. The marginal effect of US$761,839 and US$813,292 at the 25th and the 90th quantiles are both greater than the marginal effect of US$493,194 at the median. Finally, a single game of experience played over a forward's career is worth from US$426 at the 10th quantile to almost US$2,000 at the 90th quantile.

We gain additional insight into the determinants of the earnings of forwards by testing whether or not the returns to the performance measures and the other variables are statistically different across the quantiles. First, we test for the pairwise equivalence of a variable's coefficient at the θ_ith and at the θ_jth quantiles. We then test for the joint equivalence of all coefficients at the θ_ith quantile against those at the θ_jth quantile. Specifically, we test for pairwise and joint equivalence of the coefficients at the 90th quantile against those at the 10th quantile, the coefficients at the 75th quantile against those at the 25th quantile, and the coefficients at the median against those at the 90th and at the 10th quantiles. The joint tests are conducted over all the variables. The results of the tests are reported in Table 5. In the top half of the table, we find the differences in the estimates of the percentage returns from the quantile

Table 4
Typical Setting Effects for Forwards Level of Earnings Obtained From the Log-Salary Model (US$)

	OLS	Q10	Q25	Q50	Q75	Q90
GAMES	1,260	426** (.055)	995*** (.000)	1,182*** (.000)	1,745*** (.000)	1,925*** (.000)
PTSGAME	2,785,265	1,093,661*** (.002)	1,913,774*** (.000)	2,978,079*** (.000)	3,864,784*** (.000)	4,472,748*** (.000)
PIMGAME	132,904	–	–	157,579*** (.003)	153,274*** (.006)	151,287** (.086)
WEIGHT	–5,466	–	–	–6,455** (.093)	–	–
DRAFT	353,853	313,971*** (.002)	320,414*** (.000)	335,092*** (.000)	420,366*** (.000)	553,785*** (.000)
STAR	455,084	761,837** (.086)	726,954** (.039)	493,196** (.071)	426,899** (.098)	813,292** (.035)
QMJHL	–	–	–	–	–221,747 (.105)	–
USCOLLEGE				–162,714 (.108)		

Note: – = not significant; two-sided p values in parenthesis. OLS = ordinary least squares.
**Significant at 5% for one-sided t test.
*** Significant at 1% for one-sided t test.

Table 5
Joint Tests and Tests of Interquantile Restrictions for Forwards

	Interquantile Tests			
	Logarithm of Earnings (LNSAL)			
Variable	Q90-Q10	Q50-Q10	Q90-Q50	Q75-Q25
GAMES	3.70E-04 (.227)	2.84E-04 (.239)	8.62E-05 (.682)	2.38E-05 (.901)
PTSGAME	0.720*** (.079)	0.688** (.038)	–0.032 (.910)	0.333 (.295)
PIMGAME	–	–	–0.040 (.439)	–
DRAFT	–0.114 (.333)	–0.136 (.189)	0.023 (.747)	–0.057 (.399)
STAR	–0.373 (.250)	–0.403 (.179)	0.030 (.857)	–0.317 (.125)
Joint tests (*F* statistic)	1.34 (.180)	1.02 (.434)	0.90 (.560)	0.99 (.463)
	Level of Earnings			
GAMES	1,499*** (.000)	756*** (.005)	742** (.044)	751** (.014)
PTSGAME	3,379,080*** (.000)	1,884,417*** (.000)	1,494,663** (.039)	1,951,010*** (.000)
PIMGAME	–	–	–6,292 (.945)	–
DRAFT	239,813 (.164)	21,122 (.848)	218,691 (.138)	99,952 (.350)
STAR	51,454 (.925)	–268,640 (.537)	320,095 (.409)	–300,054 (.397)
Joint tests (*F* statistic)	10.81*** (.000)	4.92*** (.000)	5.76*** (.000)	6.44*** (.000)

Note: The *p* value is in parenthesis. ''–'' indicates that at least one of the estimated coefficients in the comparison was not significant at the 5% level in a one-sided *t* test. The test statistic for the pairwise comparisons asymptotically follows an *F* distribution with 1 and 392 degrees of freedom under the null hypothesis. The test statistic for the joint tests asymptotically follows an *F* distribution with 14 and 392 degrees of freedom under the null hypothesis.
*Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

regressions on LNSAL that are presented in Table 3. In the bottom half of the table, we present the differences in the marginal effects on the level of earnings reported in Table 4. In each case, the first set of statistics in the table gives the difference in the estimated coefficients and the *p* values for Wald tests of the pairwise comparison of coefficients. The second set gives *F* statistics and *p* values for the joint interquantile tests of equivalence of all coefficients at the θ_ith quantile against those at the θ_jth quantile.

It does not matter how we measure the marginal effects on earnings; the differences are not significant in any of the pairwise comparisons for the following three variables: PIMGAME, STAR, or DRAFT. For each of these variables, equivalent percentage returns across the quantiles do not translate into greater and significant changes in the level of earnings at the upper quantiles. The effect of STAR on earnings can be interpreted as a lump sum payment that is identical across the conditional distribution. Being selected in the first two rounds of the draft also has an identical effect on earnings across the quantiles. It suggests that these forwards are able to negotiate similar higher salaries in their first contracts that remain with them throughout their careers. Penalty minutes have no effect on the earnings of players at the lower quantiles and their effect is the same across the upper quantiles of the conditional earnings distribution.

For experience (GAMES), the null hypothesis of equivalent percentage returns is not rejected in any of the pairwise comparisons. However, the null is rejected in all the tests related to the changes in the levels of earnings. Equivalent percentage changes in earnings across the quantiles translate into greater and significant changes in the level of earnings as we move across the quantiles. An additional game over a player's career is worth more to high-paid players than to low-paid players.

As to the scoring proficiency of players, the percentage returns to PTSGAME are larger and the differences are significant when we compare the returns at the 90th quantile and at the median with those at the 10th quantile. The percentage returns are smaller for low-paid forwards than for the other players for whom the returns are equivalent. At the same time, the differences related to changes in the level of earnings in the transformed coefficients are significant in all the four pairwise comparisons. An increase in scoring proficiency over a player's career leads to greater and significant changes in the level of earnings as we move across the quantiles.

Lastly, joint equivalency of the coefficients is rejected in the four interquantile tests related to changes in the levels of earnings.

B. Defensemen

The OLS estimates of the earnings equation for defensemen are presented in the first column of Table 6 and they are similar to those found in the literature. Experience (GAMES, SQGAMES), PTSGAME, STAR, DRAFT, and the PLUSMINUS of a player all have positive and significant effects on the earnings of defensemen. PIMGAME, the HEIGHT and WEIGHT of players, and REVENUE are not significant. Among the junior league variables, the variable QMJHL only is significant and negative.

The quantile regressions are also presented in Table 6. The earnings equation explains more of the variation in the earnings of high-paid defensemen. The pseudo-R^2 is approximately 30% at the 10th quantile and the explanatory power of the earnings equation increases as we move along the conditional distribution to 53% at the 75th and 90th quantiles.

There are four important differences between the quantile and OLS estimates in terms of the statistical significance of the variables. First, the reputation of defensemen as measured by STAR has a significant effect on earnings under OLS but the quantile regressions show that being selected is significant only at the median and

Table 6
Quantile and OLS Estimates for Defensemen ($n = 218$)

Variable	Regression Coefficients					
	OLS	Q10	Q25	Q50	Q75	Q90
GAMES	1.47E-03*** (.000)	8.42E-04*** (.010)	1.61E-03*** (.000)	1.80E-03*** (.000)	1.70E-03*** (.000)	1.81E-03*** (.000)
SQGAMES	–1.74E-06*** (.000)	–1.21E-06 (.128)	–2.56E-06*** (.001)	–2.14E-06*** (.000)	–1.86E-06*** (.000)	–1.47E-06*** (.010)
PTSGAME	1.733*** (.000)	1.968*** (.001)	1.784*** (.000)	1.848*** (.000)	1.967*** (.000)	1.408*** (.005)
PIMGAME	–0.051 (.362)	–0.037 (.773)	–0.068 (.488)	0.041 (.549)	–0.061 (.544)	–0.025 (.830)
PLUSGAME	0.536** (.077)	0.851 (.123)	0.990** (.036)	0.344 (.361)	0.161 (.662)	0.063 (.879)
HEIGHT	0.035 (.206)	0.112** (.057)	0.050 (.291)	0.012 (.690)	0.043 (.158)	0.012 (.740)
WEIGHT	0.004 (.299)	–0.002 (.787)	0.003 (.615)	0.005 (.238)	0.002 (.721)	0.002 (.705)
REVENUE	–1.11E-04 (.955)	–3.76E-03 (.264)	–5.20E-03** (.096)	–2.43E-03 (.287)	–1.36E-04 (.954)	3.12E-03 (.266)
DRAFT	0.185*** (.010)	–0.021 (.905)	0.168 (.190)	0.226*** (.009)	0.159** (.059)	0.222** (.046)
STAR	0.568*** (.007)	0.999*** (.015)	0.757** (.051)	0.445** (.100)	0.322 (.173)	0.286 (.385)
QMJHL	–0.311** (.037)	–0.148 (.600)	–0.182 (.454)	–0.200 (.328)	–0.372** (.074)	–0.435** (.035)
WHL	–0.065 (.545)	0.057 (.775)	–0.028 (.870)	0.047 (.743)	–0.237** (.071)	–0.162 (.331)
USCOLLEGE	–0.005 (.966)	0.178 (.445)	0.057 (.732)	0.155 (.318)	–0.107 (.528)	–0.091 (.646)
EUROPE	–0.019 (.866)	0.103 (.649)	0.033 (.845)	0.192 (.223)	–0.182 (.303)	–0.155 (.461)
CONSTANT	14.143*** (.000)	13.422*** (.000)	13.909*** (.000)	14.070*** (.000)	14.589*** (.000)	14.747*** (.000)
R^2 (pseudo)	.300	.299	.399	.490	.533	.533

Note: Each continuous variable is measured in deviations from its mean. The p values for OLS are based on White heteroskedastic standard errors. The p values for the quantile regressions are derived standard errors computed from 4774 bootstraps. Two sided p values are in parenthesis. OLS = ordinary least squares.

** Significant at 5% for one-sided t test.

*** Significant at 1% for one-sided t test.

at the lower 10th and 25th quantiles. STAR has no significant effect on earnings at the upper quantiles. The results suggest that the reputations of defensemen at the 75th and 90th quantiles have already been established and STAR confirms their status without any monetary gain. Second, DRAFT has a significant effect on earnings under OLS but it has no significant effect on the earnings of players at the bottom 10th and 25th quantiles. One interpretation for this result is that defensemen who are selected early in the draft can negotiate higher initial salaries that place them immediately in the upper quantiles. Alternatively, perhaps, they negotiate higher salaries based on their draft selection in subsequent contracts only after proving themselves. Third, defensemen from the Quebec Major Junior Hockey League earn significantly less than the defensemen who played in the OHL under OLS, but the quantile regressions show that the lower earnings are significant only at the 75th and 90th quantiles. There are no significant differences in the earnings of defensemen from the QMJHL and the OHL at the other quantiles. To the extent that the differential is a result of discrimination against francophone players, as suggested in the literature,[11] it seems to exist only in the upper quantiles. Although none of the other junior hockey variables are significant under OLS, the variable WHL is negative and significant at the 75th quantile. Finally, the PLUSMINUS of defensemen is positive and significant under OLS but its effect is significant for defensemen at the 25th quantile only.[12]

The marginal effects of the variables at their average values for continuous variables and at a value of zero for dichotomous variables on the level of earnings for defensemen are presented in Table 7. In the case of a marginal change in PTSGAME, the change in the level of earnings is larger as we move from the lower to the upper tails of the conditional earnings distribution. The effect of points per game increases from US$1.3 million at the 10th quantile to US$2.4 million at the median and US$3.6 million at the 90th quantile. Under OLS, the effect of PTSGAME on earnings is equal to $2.6 million.

The marginal effect of a player's PLUSMINUS is significant at the 25th quantile only and is worth almost 1.1 million dollars compared to the estimate of approximately US$830,000 under OLS. STAR increases earnings by more than US$1.2 million at the 10th and 25th quantiles and by US$700,000 at the median. The estimated value at the lower quantiles is greater than the value of US$880,000 obtained under OLS. A DRAFT is worth approximately US$350,000 for defensemen at the 50th and 75th quantiles and more than US$630,000 at the 90th quantile.

Defensemen who played their junior hockey in the QMJHL earn approximately US$1.1 less than those who played in the OHL under OLS. The results from the quantile regressions show that the lower earnings are significant at the upper quantiles only where the differential is approximately US$674,000 and US$896,000 at the 75th and 90th quantiles. At the same time, defensemen from the WHL earn approximately US$457,000 less than defensemen from the OHL at the 75th quantile.

The results of the Wald tests on the equivalence of the parameters across quantiles are presented in Table 8. In the top half of the table, we find the differences in the

Table 7
Typical Setting Effects for Defensemen Absolute Terms From the Log-Salary Model (US$)

	OLS	Q10	Q25	Q50	Q75	Q90
GAMES	2,272	568** (.047)	1,769*** (.000)	2,316*** (.000)	3,682*** (.000)	4,598*** (.000)
PTSGAME	2,685,936	1,327,872*** (.008)	1,960,233*** (.001)	2,383,086*** (.000)	4,264,723*** (.000)	3,575,759*** (.011)
PLUSGAME	830,191	–	1,087,815** (.049)	–	–	–
HEIGHT	999	75,462** (.077)	–	–	–	–
DRAFT	286,485	–	–	326,347** (.018)	374,315** (.050)	630,848** (.045)
STAR	880,775	1,156,846* (.117)	1,243,473* (.168)	722,447* (.181)	–	–
REVENUE	–	–	–5,713** (.080)			
QMJHL	–482,344	–	–	–	–673,992** (.079)	–895,964** (.050)
WHL	–	–	–	–	–457,361** (.096)	–

Note: – = not significant; two-sided p values in parenthesis. OLS = ordinary least squares.
* Significant at 10% for one-sided t test.
** Significant at 5% for one-sided t test.
*** Significant at 1% for one-sided t test.

Table 8
Joint Tests and Tests of Interquantile Restrictions for Defensemen

	Interquantile Test Statistics			
	Logarithm of Earnings (LNSAL)			
Variable	Q90-Q10	Q50-Q10	Q90-Q50	Q75-Q25
GAMES	9.69E-04** (.024)	9.54E-04*** (.005)	–1.52E-05 (.959)	8.74E-05 (.770)
PTSGAME	–0.559 (.443)	–0.119 (.841)	–0.440 (.408)	0.183 (.725)
DRAFT	–	–	–0.004 (.975)	–
STAR	–	–0.554 (.1815)	–	–
Joint tests	1.40 (.157)	1.310 (.204)	0.82 (.647)	0.63 (.835)
	Level of Earnings			
GAMES	4,031*** (.000)	1,747*** (.000)	2,283** (.028)	1,913*** (.009)
PTSGAME	2,247,887 (.120)	1,055,213 (.135)	1,192,674 (.377)	2,304,490** (.030)
DRAFT	–	–	304,501 (.315)	–
STAR	–	–434,399 (.576)	–	–
Joint tests (F statistic)	4.17*** (.000)	4.11*** (.000)	1.43 (.143)	2.23*** (.008)

Note: ‘‘–’’ indicates that at least one of the estimated coefficients in the comparison was not significant at the 5% level in a one-sided t test. The test statistic for the pairwise comparisons asymptotically follows an F distribution with 1 and 203 degrees of freedom under the null hypothesis. The test statistic for the joint tests asymptotically follows an F distribution with 14 and 203 degrees of freedom under the null hypothesis. The p values are given in parenthesis.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%

estimates of the percentage returns from the quantile regressions on LNSAL that are presented in Table 6. In the bottom half of the table, we present the differences in the marginal effects on the level of earnings reported in Table 7.

It does not matter whether we use logs or levels to measure the returns, the differences are not significant in any of the pairwise comparisons for two variables: STAR and DRAFT. STAR has a significant effect on the earnings of defensemen at the lower 10th and 25th quantiles and the median. The effect on earnings, however, is identical across these quantiles and can be interpreted as a fixed lump sum payment. There is no relationship between earnings and DRAFT at the lower quantiles. However, an early selection has the same effect on earnings of defensemen at the median and upper quantiles.

As to PTSGAME, we cannot reject the null hypothesis of equal percentage returns across quantiles. In the tests related to the changes in levels of earnings, the null is rejected only in the pairwise comparison of the 75th and the 25th quantiles. The results of the statistical tests suggest that an increase in the scoring proficiency of defensemen is identical across the quantiles.

As to the marginal effect of experience, the percentage returns are smaller for low-paid defensemen than for the other players. The percentage returns for the variable GAMES are larger and the differences are significant when we compare the returns at the 90th quantile and the median with the returns at the 10th quantile. The differences in the percentage returns are not significant in the other pairwise comparisons. At the same time, the differences in the marginal effects of experience on the level of earnings are significant in all the four pairwise comparisons. Therefore, the value of additional experience over a defenseman's career increases as we move along the conditional earnings distribution.

Finally, the joint equivalence of the coefficients is rejected in all the interquantile tests related to changes in the level of earnings.

Concluding Remarks

Most studies on the determination of player earnings in the NHL estimate earnings equations in the conditional expectation framework. Our OLS estimates of the earnings equation for the 2003-2004 season are consistent with the results of these studies. Using measures of performance over a player's career, we find that experience, PTSGAME, STAR, and DRAFT all have positive and significant effects on the earnings of forwards and defensemen. Penalty minutes per game also have a positive effect on the earnings of forwards. The PLUSMINUS is a significant determinant of earnings for defensemen. In addition, we find that defensemen who played amateur hockey in the Quebec Major Junior Hockey League earn significantly less than defensemen from the OHL.

The earnings determination process in the NHL turns out to be much more complex than the one described by the conditional expectation model estimated by OLS. Using quantile regression, we show that the parsimonious empirical specification of the earnings equation using career statistics explains much less of the variation in the earnings of low-paid players than high-paid stars.

We also find that penalty minutes per game are a significant determinant of earnings for forwards only at the upper quantiles of the conditional earnings distribution. We also find that an additional single game played or a marginal increase in the number of points scored per game has a greater effect on earnings as we move up the conditional earnings distribution.

For defensemen, STAR increases the earnings of players only for players at the lower quantiles, while DRAFT has an effect on earnings only at the upper quantiles. We also find that defensemen from the QMJHL earn less than defensemen from the OHL only at the upper quantiles of the earnings distribution. In addition, the effect of the additional experience of a single game on the level of earnings is greater at the upper quantiles than at the lower quantiles.

Notes

1. For a survey of the literature, see the survey chapters in Fizel (2006).

2. Measuring the performance of players in hockey can also be problematic because of the effect of teammates on performance. Idson and Kahane (2001) and Kahane (2001) provide empirical evidence that higher quality teammates lead directly to higher earnings for players and to greater returns for some measures of individual performance. We do not examine this issue in this article.

3. Jones et al. (1997) examined this question using two separate OLS equations characterizing players as ''grunts'' and ''nongrunts.'' They found the structure of salaries is different for each group but there is no resulting effect on the total salary earned by the ''grunts.''

4. See Schulze (2004) for an exhaustive listing of empirical studies using quantile regression.

5. We also used team wealth instead of team revenue as an explanatory variable. Our estimation results were not affected.

6. We would like to thank an anonymous referee for this suggestion.

7. We excluded two players from our sample. The first player was excluded because he is part of the ownership group; his team and his reported salary may not be entirely related to his performance. The second player was excluded because he signed a contract with a new team for the 2003–2004 season as a free agent for a salary substantially less than the one that he could have obtained from his previous team or from the market.

8. The estimation process was carried out using the sqreg procedure in Stata. Standard errors of the coefficients are obtained using the design matrix bootstrap and the variance–covariance matrix includes between-quantile blocks. The number of bootstraps was determined by an algorithm proposed by Andrews and Buchinsky (2000) and implemented in Stata using the procedure bssize described in Poi (2004).

9. If the error term is not normally distributed, the expectation of earnings is proportional to the exponential of the prediction of the log of earnings, $E(SAL|x) = s\ \exp(\ln SAL)$, where $s = E(\exp(\mu))$. Homoscedasticity is assumed in both cases.

10. Estimates and statistical tests related to changes in the level of earnings were obtained using the nlcom and test procedures in Stata.

11. See Jones et al. (1999); Lavoie (2000); and Curme and Daugherty (2004) for a recent discussion.

12. To test for the potential entry discrimination against QMJHL players, we removed the draft variable from the estimations—the results for QMJHL players are virtually the same. See Lavoie (2003) for a discussion on entry discrimination with respect to francophone players.

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