DYNASTY DISCOUNT:

INTER-TEAM DIFFERENTIALS IN NHL PLAYER COMPENSATION

by

Benoît Stooke
B.A. Simon Fraser University, 2006

PROJECT SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF ARTS
in the
Department
of
Economics

SIMON FRASER UNIVERSITY
Summer 2008

APPROVAL

Name: Benoît Stooke

Degree: Master of Arts

Title of project: *Dynasty Discount:* Inter-Team Differentials in NHL Player Compensation

Examining Committee: Arthur Robson,
Professor, Department of Economics
Chair

Simon Woodcock, Senior Supervisor
Assistant Professor, Department of Economics

Philip Curry, Supervisor
Assistant Professor, Department of Economics

Jane Friesen, Internal Examiner
Associate Professor, Department of Economics

Date Approved:

Abstract

In recent years, a lot of work has been done to study the effect of firms in wage determination. In fact, firms have been found to contribute a great deal to intra-industry wage differentials. This paper uses NHL player and team data to examine the importance of inter-team differences in NHL player compensation. Using information from various sources, an analysis of player salaries for the period 1998-2004 is done using a standard wage regression with fixed player and team effects. What we find is that in the NHL, team effects are not generally important in of player compensation. However, the teams with statistically significant team effects exhibit characteristics often associated with dynasties.

KEYWORDS: National Hockey League, player salaries, dynasty, person and firm effects, fixed effects.

To Daniel Alfredsson, a true leader and local hero;
To the Garbage Bears, against all odds;
To my friends and family.

Acknowledgements

I wish to thank my all friends throughout my university career, and without whom it surely would have been a different story written for me. From everyone who's helped me getting adjusted in my early days to those I've worked with over the years and my fellow students in the economics department.

I am especially grateful for Dr. Simon Woodcock's support and help with my work, it was not given away. I've learnt quite a bit and have gained a new appreciation for labour economics. And a great thank you to Dr. Philip Curry for his help and insight, it has given me good ideas.

Lastly, my parents who have supported me through all the ups and downs and who were always there for me through thick and though. *Merci pour tout!*

Contents

1 Introduction

When firms possess some level of monopsony power in contract negotiations, they may be able to extract wage concessions from workers. On the other hand, if workers have alternate opportunities, they may be able to extract rents from rich firms. One rich industry that provides a more or less closed and complete labor market with high worker mobility is that of professional hockey. One can see players as scarce and possibly able to extract rents from teams, and simultaneously expect teams to be able to provide unique characteristics associated with their own franchise. In this case, we might observe differences across teams in player compensation based on the rents available and specific market or franchise characteristics, even controlling for player performance.

So, are such inter-team differences in compensation present in a standard wage model for professional hockey players? And if so, can we identify some of the influential factors explaining such persistent differences in compensation? The interest in the question is that it can help determine whether teams (firms) have to compensate players (workers) for poor market characteristics (i.e. location) and/or if they can attract players at a discount when endowed with positive or favorable conditions. To my knowledge, this is the first paper to tackle this issue for a professional sports industry. Work has been done on this subject with respect to other labor markets, but with the distinct special status of professional sports, the small number of teams, high mobility and the presence of a powerful all-encompassing union, it presents a special and interesting case in the context of firm effects in wage determination.

In this paper, I use data for professional hockey players in the National Hockey League (hereafter NHL) where we can easily observe performance and identify player mobility and team association. This facilitates the observation of a compensation/discounting effect based on the signing team, when controlling for measured and unmeasured skills. The main question is whether or not there are teams paying significantly above or below the league average for players. This paper studies these effects by empirically estimating a wage regression model that includes fixed team effects.

I find that team effects account for a surprisingly small portion of overall compensation variance — much less than firm effects account for in the broad labor market. But I do find a small number of teams paying substantially different from league average; most interestingly, those teams are associated with consistent post-season success and a high rate of returning players. The results suggest that players are not only willing to earn less to be on a winning team (a championship discount), but that they want to be part of a dynasty-type team, thus the observation of what I call a *dynasty discount*.

The following is the structure of this paper. In section 2, I do a quick literature review of relevant models and also establish a theoretical motivation of why we might expect to observe persistent team differences across teams in player compensation. In section 3, I outline the model used throughout this paper. Section 4 is an overview of the data used, the sources, and its distribution. Section 5 focuses on interpreting the results and comparing to other works. I conclude with a brief summary of the results and their implications.

2 Motivations

Literature Review

Until recently, there had been little empirical work done with regards to salary determination in the National Hockey League (NHL). In a recent paper, Haisken-DeNew & Vorell (2008) mention the rarity of economic research regarding professional hockey as compared to other major professional leagues, and briefly outline some of the topics covered. The major (and oldest) issue covered is salary discrimination, especially with respect to French-Canadian players. Jones & Walsh (1988) and Longley (1995), among others, look at this particular issue. Where Jones and Walsh find no evidence for discrimination, Longley finds some but only for teams based in English-Canada.

Haisken-DeNew & Vorell (2008) try to answer the less asked question of how on-ice violent behavior affects compensation and team performance. Consistent with expectations, they find that violent behavior is rewarded with monetary incentives and more importantly fights become a major determinant of salary for certain types of players called enforcers. They look at the impact of violence (proxied by penalty minutes and fights) on the success of a team and on the compensation of players, mostly enforcers.

The central question in these papers is how team management decides to reward individual performance. Only minor work has been done looking at *team* characteristics in salary determination. Jones & Walsh (1988) consider some characteristics such as income and population as factors in determining compensation but find that they have no significance. Outside the NHL, Idson (1995) suggested that team production could be important in worker compensation. His work showed that earnings of nonunion workers were positively related to group size, encouragement to work in groups, as well as the effectiveness of the team. Following this idea, direct work (Idson & Kahane 2000, 2004) has transposed the principle to professional sports using NHL and NBA data for not only player and team performance but also for coaching and interaction terms. The goal was to answer whether players gained from playing on good teams; simply put, if chemistry added to compensation. The results were that the teammate effect was positively significant in both leagues. Taking the idea of some type of team/player effects in salary determination further, Kahane (2001) used a random coefficients model to show that there is a significant difference in how teams reward players and team revenues can partially explain that difference.

But even further, something that has emerged in the labor literature and has yet to be transposed to the sports world, is the role of unobserved worker and firm characteristics in compensation. A lot of recent work has focused on the importance of such fixed individual and firm effects, and shown how to estimate them (Abowd et al. 2002; Woodcock 2007, 2008). The idea is that there are unobserved worker and firm characteristics helping to determine wages and they can explain a substantial fraction of observed wage variation: unobserved worker characteristics are typically found to explain 35-55% of total variation and unobserved firm characteristics explain 15-25% (Woodcock 2008). These unobservables have traditionally been left out of labor models but some authors (see Groshen 1991; Idson 1995) suggest that employers and coworkers account for a significant portion of intra-industry wage differentials. In the sports industry, some of this matching effect can be represented as teammate performance (as in Idson & Kahane 2000, 2004, for example). Unobservable worker characteristics (or player effects) can be thought of as grittiness[1], on-ice effort and leadership. As for unobservable firm characteristics (team effects), one can think of management and coaching structure, development and training programs and even market and community characteristics. Obviously these effects could vary over time and there is significant reason to believe they will do so as a franchise grows and develops and even the industry as a whole changes, but it is also believable that in the short term, these player and team characteristics will be fixed.

It is a common belief among fans that, in the world of sports, salaries are the main (and possibly only) determinant of how teams attract players. The concept being that for a player with a given level of skills, the team with the highest marginal revenue product will offer the highest wage. In some cases, a team might offer significantly more than 'market value' to not only sign the player but also to prevent opponents from signing that particular player,

[1] Defined as 'courageously persistent' (The Merriam-Webster Dictionary 2005).

even if at the margin he is worth less to the richer team. Out of this concept was coined the idea of "buying a championship", as was widely associated to rich teams in various leagues (Major League Baseball's Yankees being the leading example).

But what if money is not the only determinant of player compensation? What if there are other team characteristics at play that help a team pay less or forces another to pay more?[2] To understand how this can come into effect, I must first turn to the structure of the NHL and how wages and contracts are determined. NHL teams and players are bound to rules and regulations as determined by a Collective Bargaining Agreement (CBA) negotiated and agreed upon by the NHL (representing all owners) and the NHL Players' Association (NHLPA, representing all players). The CBA imposes restrictions on how teams and players are allowed to negotiate with each other and it establishes a standard player contract. Established players without a contract will generally fall into either of two categories, unrestricted free agents (UFA) and restricted free agents (RFA). Unrestricted free agents are allowed to negotiate a new contract with whomever they want according to the guidelines established in the CBA. On the other hand, restricted free agents are limited in their movement. Even though they are allowed to negotiate with other teams, it comes down to their current team to decide if they will take on a contract signed with another team or if they will let the player go, in which case the signing team must compensate the current team based on the salary agreed to with the player. In a sense, players are auctioned on the free agent market with teams making offers and the players bargaining with various teams and signing with a team offering the highest value to the player.

From the team's perspective, an offer will be based on a player's skills (estimated by past performance), and how much his on-ice product will attract fans and sponsorship and thus increase revenue. A team will have a maximum willingness to pay that is equal to the player's marginal revenue product to the team as determined by a team-specific revenue function. I would expect teams in richer markets to have a higher MRP and be able to

[2]This study predates the new era of salary caps, including a hard cap structure introduced in the NHL in 2005. Salary caps impose restrictions on how much teams can pay their players. With these restrictions on player expenditures (for the whole team and individual players), teams will, supposedly, no longer be able to spend ludicrously on players.

offer more to a player. From the player's perspective, an offer will be accepted when it maximizes his expected utility. It is therefore relevant to assume that players not only look at the monetary value of the contract but also consider non-monetary incentives or disincentives such as climate, the chance of winning a championship, quality of life, etc. Since these characteristics vary across teams and markets, it is reasonable that a player will have different minimum salaries he's willing to accept for any given team making an offer.

The above situation endows both parties with bargaining power. On one hand the teams have monopsony power in their own market and have specific characteristics possibly attractive for some players, and may therefore seek wage concessions from players justified by higher player utility. On the other hand the player has a given skill set that he can sell to other teams (albeit a small number) and therefore he may have an alternative wage available. A player may seek to extract rents from richer teams based on marginal revenue product. What I would expect from this is that beyond performance, revenue and utility factors could also be determinants of player salaries. Since teams are heterogeneous across the league, in terms of characteristics and revenues, one would expect to see contracts across teams to display systematic differences in compensation. This hypothesized systematic variation is what I focus on estimating and explaining if, in fact, I do observe significant differences across teams.

3 The Model

Given the reasoning presented earlier to suggest the presence of both unobserved player and team effects in compensation, the empirical model includes fixed player and team effects, as was originally presented in Abowd et al. (1999). Because of the relatively short period (six seasons) used, it is reasonable to assume time-invariant effects, making the estimation of fixed player and team effects easier. With a significant rise in average real salaries from \$1.56 million in 1998/99 to \$2.06 million in 2003/04 (33% growth over 5 years), it also sensible to include a season indicator to compensate for increasing base salaries. Thus the model I estimate is:

$$\begin{aligned} \ln y_{it} &= \mu + x'_{it}\beta_1 + z'_{jt}\beta_2 + \theta_i + \psi_j + \delta_t + \epsilon_{it} && (1) \\ \theta_i &= \alpha_0 + u'_i\alpha_1 + \alpha_i && (2) \\ \psi_j &= \eta_0 + v'_j\eta_1 + \eta_j \quad | \quad j = \mathrm{J}(i,t) && (3) \end{aligned}$$

where y_{it} is player i's salary[3] at time t in real (2003) dollars; x_{it} and z_{jt} are vectors of time-varying player and team performance characteristics; θ_i and ψ_j represent player i and team j time invariant-heterogeneities with $j = \mathrm{J}(i,t)$ being player i's team during season t; and δ_t is a seasonal effect to compensate for league-wide growth in salaries. In equations (2) and (3), I decompose fixed player and team effects into their observed and unobserved components. Here, u_i and v_j are the time-invariant observable player and team characteristics; and, α_i and η_j are the returns to unobservable player and team characteristics. It should be noted that both fixed player and team effects are estimated as deviations from the league mean.

Since forwards and defensemen have different roles, it is believable that each type of player will be rewarded differently for their performance. But, as well, I want to restrict the team effect, ψ_j, to be the same for all players on team j. So instead of using two different regressions, the performance statistics are interacted with a position indicator: $I_f = 1$ if the player is a forward, $I_d = 1$ if the player is a defenseman. That is, I redefine

[3] Salary represents total compensation including performance and incentive bonuses, and a prorated signing bonus.

$\tilde{x}_{it} \equiv [I_f x_{it} \quad I_d x_{it}]$ and $\tilde{u}_i \equiv [I_f u_i \quad I_d u_i]$. The only performance measure that will not be interacted is the number of trophies. Since there are only a few trophies awarded per season and most are already taking into consideration the player's position, it is sensible to consider the presence of trophies regardless of position. I also keep league experience un-interacted and the assumption made here is that the value of a year of professional experience is equivalent across positions.

I should note that I include quadratic *experience* to appeal to standard human capital models (Mincer 1974). This allows for decreasing returns to experience. For the same reason, I include a quadratic in *career trophies* as well. That is, trophies represent a superior performance but a sustained high caliber performance may not have a significantly larger compensation year after year. The remainder of performance statistics are expected to have linear returns.[4]

The first model I estimate is a simple wage regression including player and team fixed effects (θ_i, ψ_j) and player performance statistics (x_{it}). That is, I estimate equation (1) without time-varying team characteristics (z_{jt}), and establish the presence of team heterogeneity in salary determination. After doing a quick analysis of these first results and those provided from equation (2), the next model looked at and interpreted more deeply will be the joint model of equations (1) and (3), where I add time-varying team characteristics to equation (1) and observe whether the significance and magnitude of the team effects declines, and if these components are themselves significant in the wage regression.

[4] I have considered quadratic returns for both goals and assists, and the results display a lower precision without affecting the distribution of the other components.

4 The Data

The data used in this paper come from various public sources. Player performance and characteristics as well as team performance come from the official NHL website[5]. Data on arena and market characteristics were taken from Ballparks.com[6] while salaries, attendance, fan cost index and team finances were provided by Rodney Fort[7] with the original sources ranging from *Forbes* (income and expense) to *Team Marketing* (fan cost index) and the *Sports Business Journal* for some attendance figures. Fort also mentions "popular sources" as an information source.

The timeframe spans the 1998-99 to 2003-04 seasons, roughly a full CBA. The CBA in use during that period was implemented in January 1995 and expired in June 2004. It was amended in June 1997, which makes the 1997-98 season the only missing year from the data covered by the amended CBA.

I impose several restrictions on the data to obtain a sample of players for whom wage determination is plausibly homogeneous. I exclude rookie players, as their contract terms are often predetermined by league regulations. Depending on the player's age at the time of signing, rookie contracts can last up to three years, and because unrestricted free agency is obtained after at least 4 years experience, I put a restriction on experience of at least three years. This restriction removes rookies but includes restricted free agents who have some limited bargaining power when negotiating salaries, unlike rookies.

I also exclude players with a weak attachment to the league or team, that is players who often get called up from and sent down to the farm teams, traditionally the American Hockey League or AHL (hereafter referred to as *call-ups*). To filter out call-ups, I want to establish a reasonable threshold of games played that would give a more complete representation of a player's performance. Players on a "two-way" contract, are paid a different salary when playing in the AHL than in NHL. But if a player qualifies for an "accrued" season, they are

[5] www.nhl.com

[6] www.ballparks.com

[7] www.rodneyfort.com

paid their full NHL salary. Looking at the CBA, it defines an "accrued season" as:

> "... [a year] during which a player was on a Club's Playing Roster for 40 (30 if the Player is a goalie) or more regular season NHL games, provided that, for the purposes of calculating an Accrued Season under this Agreement, games missed due to a hockey-related injury incurred while on a Club's Playing Roster shall count as games played for purposes of calculating an Accrued Season but only during the League Year in which the injury was incurred and a maximum of one additional season." (CBA 1997)

It is fair to assume that players playing less than 40 games will generally be call-ups since teams will opt out of paying them their full NHL salary. Restricting the data to 40 games played would significantly reduce the sample. Given that my measure of games played comes not from the Playing Roster, but rather actual games dressed for and played in, games missed due to injury are not accounted for. Those can often amount to 10 or more in a full season. For this reason, I impose a restriction of 30 games played rather than 40. Players dressed for 30-40 games should still be representative of low caliber players.

Table 1 shows the means and standard deviations for the player performance statistics and characteristics by position type (forward or defenseman). Performance statistics are lagged one year in the regression model, since teams will use past performance to predict future performance when they negotiate the player's contract. I use 'per game' performance statistics to adjust for potential injury/call-up factors. It measures players' performance for the portion of the season actually played in, and allows a better estimate and interpretation of the coefficient observed on *games*. As to why I am using *career trophies*, it is a measure of cumulative and sustained performance, and it compensates for the low number of awards given out each year. A sustained performance should be a good predictor of future performance whereas a single trophy might just indicate a 'lucky' year. The *European* and *Quebec-born* variables are entered as indicator variables equal to 1 if the characteristic is satisfied. The displayed statistics thus give the percentage of the sample characterized by this indicator, obviously these are mutually exclusive. It shows that roughly 30% of players are European (more prominent on defense) while Quebec provided 10%, with a slight favoritism for forwards. I include these indicators to be consistent with earlier results (Jones & Walsh 1988; Longley 1995) showing potential discrimination for Quebec players. The inclusion of a European indicator is to represent the changing composition of the league as more and more European players join the NHL.

Table 2 presents a similar display for the various team characteristics used in the models. The first category shows the average success record. The *regular season record* is simply the proportion of points gained in one season. A season is 82 games with a maximum of 164 points attainable (2 points per game). A win is 2 points and a tie is 1 point. A 50% record indicates a team received 82 points, which could be 41 wins and no ties, or a combination of both. A mean of 53% is obtained because during that period, the three points game came into effect, where an overtime loss would result in a single point and thus three points awarded for a single game.

The *historical success rate* is a custom built index to represent consistency in a team's post-season success. It spans the five previous seasons and associates a different value to different levels of success. Since a 100% success would be associated with 5 Stanley Cup wins, a championship consists of 20 percentage points. Since every level of success is more significant than the next, the gains to greater success should be increasing; as presented by the structure of Table 3. The current *historical success rate* (H_{jt}) is the accumulation of the yearly indices over 5 years, $H_{jt} = \sum_{i=1}^{5} p_{j,t-i}$. Using this index as opposed to simply accounting for the number of times a given post season round has been reached helps us rank teams in terms of historical performance.

The following characteristics are direct and indirect measures of the team's potential and realized financial successes. All financial figures are in real terms (base 2003). Seating capacity, population base and the fan cost index[8] represent potential revenue because they are static regardless of attendance. I would expect a positive effect from these as they

[8]Fan Cost Index, as estimated by Team Marketing, comprises the prices of two (2) adult average-price tickets, two (2) child average-price tickets, two (2) small draft beers, four (4) small soft drinks, four (4) regular-size hot dogs, parking for one (1) car, two (2) game programs and two (2) least expensive, adult-size adjustable caps.

represent potential marginal revenue and therefore should influence the salary offered by the team. *Revenue* and *attendance* are measures of realized successes, primarily financial but also in terms of on-ice product; a performing team attracts more fans thus higher attendance and viewers, which increases revenues. I expect a positive coefficient for revenue as it is a direct measure of actual marginal revenue, but as for attendance I can argue the case that it influences both marginal revenue and utility. Higher attendance is no-doubt associated with greater financial success, but it can also be a sign of popularity and an environment a player would prefer to play in. *Other expenses* represents the non-player expenditures. I expect a negative sign for this component as it can indicate the team has more non-player spending and thus less to give to players, but also is could mean that a team is spending more to make the players better and more comfortable and players would benefit directly from this. The *market income tax rate* is the personal income tax in the relevant market that a player will have to pay. Its inclusion reflects the potential need for teams to compensate the player for a higher tax rate in their province/state. It includes both the federal and provincial/state tax rates for the highest income bracket, which varies from \$65,000 to \$130,000 depending on the market. This is still lower than the average established professional hockey player salary.

Other characteristics I include in the model relate to the age of a franchise in a market and current playoff performance. In the data there is the addition of four new teams: Nashville (1998), Atlanta (1999), Columbus (2000) and Minnesota (2000). As well, there are relatively recent relocations such as Phoenix (1996 from Winnipeg) and Carolina (1997 from Hartford). To control for the lack of an established fan base in those markets, I create an indicator, *recent*, to categorize the relatively new teams. *Recent* is equal to one if the team is in its first 4 years of existence or its first three years after relocation. This difference of one year is to compensate for the fact that a relocated team already had an established organization in place as opposed to a new start-up that has to create this structure.

The current season playoff performance indicators are simply variables equal to 1 if the team appears in the conference finals (3rd rank), the Stanley Cup finals (2nd rank), or wins the Stanley Cup (1st rank) $[I_3\, I_2\, I_1]$. A team winning it all would have a $[1\,1\,1]$ vector of indicators. These indicators are introduced because players will sometimes receive incentive bonuses based on how long the team lasts in the playoffs.

Players occasionally change teams mid-season. In these cases, the team I associate with the player's wage record in that season is the team with which they began the season since this is the team with whom the wage contract was negotiated.

5 Results

5.1 Baseline Model

The baseline model is the wage regression excluding time-varying team characteristics. The results from Regression 1 in Table 4 give an interesting picture of compensation in the NHL. As expected, the returns on *experience* are positive but the rate of compensation is decreasing (although small in magnitude) with increased experience. The returns to experience above 3 years are roughly 30%. As well, the hypothesis of decreasing return with accumulated *trophies* is also confirmed, with a faster rate of change than for *experience*. It tells us that earning the top performance in a given season (indicated by a single trophy) should lead one to expect a 42% increase in salary.

Turning to interacted performance statistics, it shows different rates of compensation for both types of players. Similar results are presented for *assists per game*, *blocks per games*, *time on ice per game* and *plus/minus*. Increasing performance and ice-time should indeed lead to higher returns since higher performance in points helps the team win and greater ice-time suggests an increased role on the team and increased demand for the player's labor. When it comes to *blocks*, I could expect different results for forwards and defensemen. One can think of blocking as a strong defensive play (known as the "art of blocking shots") and therefore should lead to increased compensation for defensemen but not for forwards given the risk of injury. Instead I observe a significant 13-20% decrease in salary associated with increased blocked shots per game, suggesting that this role should be left to the goaltenders rather than skaters. It should be noted that the coefficient is smaller for defensemen, leading to the interpretation that they are less penalized for engaging in this behavior. The last common coefficient is associated with the defensive statistic *plus/minus*, which shows near-zero negative returns (10% significance level for defensemen). Again as it is a measure of defensive play, this is not surprising for forwards but it is a statistic that was implemented to help measure a defenseman's performance.

Looking at the rest of the coefficient for forwards, the single most important one is *goals*. The results show that a player scoring an extra goal every game (totaling up to 82 goals a season) should expect a reward of 50% above the rest. But this can go down if such a player is too physical. A rise in a player's *hits* can certainly increase the risk of injury and therefore an expected 7.5% decrease in compensation. Increases in *penalty minutes* and *games played* do not have a large or significant impact on compensation. A player should be expected to play by the rules and not take stupid penalties but also, they should be expected to prevent a scoring chance by any means necessary if need be, the results show that these concepts may cancel each other. As for games, it might be surprising to see no significance, but it can be explained by the notion that forwards should play a significant role every game (ice-time) and that increases in games played should also be associated with increases in measured performance.

In the case of defensemen, it is in accordance with expectations that *goals* do not play a significant role in compensation. It is not their primary role, but I should specify that the returns on assists for defensemen are 10% higher than for forwards. As for *hits*, again this is slightly uncharacteristic of what one might expect. A defenseman's role is to hit. Just as for forwards, hitting may lead to increased penalties or injuries. There is no strong reason to explain the lack of significance here but the idea of two opposite effects canceling out may be in play.

Contrary to forwards, *games played* plays a significant role in defensemen's compensation, albeit small in magnitude. This may suggest that, unlike forwards, defensemen have a less measurable role on a team. As they play more games, their role is greater but cannot be measured strictly by statistics available, it would then be reflected in the increase in games played. Concerning the magnitude of the coefficient, one must note that if a defenseman is given a bigger role on a team, the number of games played would increase by a number significantly higher than 1, more like 20 for example. This increase of 20 games played is associated to an expected increase in salary of 4%. This increase is 8% if a defenseman goes from playing a half-season (41 games) to playing a full season (82 games).

Looking at the year effects, I'd expect an increase in salaries over time, but what is observed are insignificant and negative coefficients. This might be counter-intuitive as I've shown earlier that average salaries increased over the sample period. In the top of the salary distribution (above \$ 5 million) we see significant growth in salary over time (average yearly increase of 30% in real terms) but measured performance (goals and assists) of these players is relatively static. In contrast, below the \$5 million mark (about 90% of players) there is slower salary growth over the sample period (about 20% in real terms) but performance measures increase substantially over time (about 30%). This breakdown suggests that the increase in average salaries over time has of two different causes. The first one is that a few high paid players drive the average up. The second one is that the majority of players have increasing per game performances, capturing some of the increase in salaries.

When looking at the distribution of player effects (θ_i) in Table 5, there is a vast range of player effects, from -2.37 to 1.74. This suggests a strong variation in unobservable performance. This can include characteristics that I had expected but not observed in the results discussed above. For example an "enforcer" might be compensated for certain types of penalties taken, but since the rule does not apply to every player, this is not observed in the coefficient on penalties. If I could identify all enforcers and include a categorical variable in the model, I would be expected to extract this effect from θ_i. Another component that can be considered part of θ_i would be the aforementioned "art of blocking shots". Someone who blocks too many shots needlessly would probably be expected to be injured often and receive a lower salary, but a defenseman who has this specific talent (Mike Komisarek, Anton Volchenkov and Jason Smith all block well over 100 shots in any season) and knows *how* to do it properly can expect an increased salary as it does reduce scoring chances. θ_i also takes into account leadership, grittiness and other personality traits not observable or measurable.

For curiosity purposes, Table 6 consists of the top and bottom 10 players as ranked by their estimated fixed effects. We might consider them to be the most 'overpaid' and 'underpaid' players in the league. We could also think that these represent the players with the most and least valuable unmeasured skills. When we look at the names in the top ten table, we observe superstars who earn high salaries often with the argument that they bring "something more" than performance to the team, an intangible. Ottawa Senators fans may argue that Alexei Yashin's "something more" may actually be undesirable and that he is just an overpaid superstar! One might consider that the quality of the top ten might suggest misspecification in the model, possibly due to increasing returns to performance. But as I stated when describing the model, I have considered quadratic terms for goals and assists and the distribution of player effects and the composition of top 10 remains identical, indicating that misspecification is not the cause. The bottom 10 table is comprised mainly of average players who come to the game, play and go home; although the table does include household names like Guy Carbonneau and Ed Olczyk.

When breaking down the player effect into time-invariant observable player characteristics, I get the results shown in Table 7. The measures of height and weight are in deviations from sample mean. What the results show is that forwards and taller players are compensated more and Europeans are paid a premium, which could be due to them leaving their country to play in the NHL. Heavier defensemen are also paid more, this most likely is a representation of their strength and ability to drive opponents off the puck. And finally, Quebec-born defensemen are paid less, consistent with earlier works mentioned (Jones & Walsh 1988; Longley 1995), and potential evidence of discrimination.

Also displayed in Table 5 is the summarized distribution of team effects (ψ_j), showing a small variance over a large range. Table 9 shows the full spectrum of team effects as deviations from a league average salary. Obviously, as they are deviations from the league average, their average should be zero, and this is in fact observed. The range of ψ_j spans nearly 40% with no single team having a statistically significant deviation from the mean. The estimates show some teams paying 19% below the average (Detroit) and others being above by 18% (New York Rangers).

One interesting way to look at the results is to consider the correlation table presented in Table 10. Obviously, looking at the correlation between a player's performance (observable and unobservable) and compensation, one should expect a strong positive one, as is observed from the various correlations including $x\beta$, θ_i, and $\ln y_{it}$. What is not so clear is what I should expect for correlations involving ψ_j. The results from Abowd et al. (2003) and Andrews et al. (2008) suggest that I should expect a negative, or at least zero, correlation between θ_i and ψ_j, unobservable player and team effects. Abowd et al. present correlations of 0.02 and -0.24, for the United States and France respectively, while Andrews et al. cite various researches with similar numbers. Andrews et al. suggest that this estimated correlation is biased downward the less mobility in the industry. Given the high mobility of players (estimated at around 20% in any given year) through trades and free agency, the bias is probably small in NHL data. The results are not only consistent with these findings, the correlation is -0.099, but also they show zero correlation with the observable performance. Moreover, there is a positive correlation between log wages and ψ_j, high paying teams thus consist of high paid players, which is easy to believe. One interesting note is the strong negative correlation between observable and unobservable player characteristics. This suggests two kinds of skill, measured and unmeasured, and that players typically specialize in one or another. The superstars mentioned in Table 6 may be part of a group possessing both, which would explain their superstar status.

A decomposition of variance like that discussed in Woodcock (2008) is presented in Table 11. The decomposition gives the proportion of the variance of log compensation attributable to the relevant components. As one should expect, performance provides 67% of the variance in log compensation. Player effects (θ_i), contribute another 25% while my component of interest, the team effect (ψ_j), contributes less than 1%. There is a stark contrast to the 16% found in Woodcock for the United States (US Census Bureau LEHD data). The results shown here seem to indicate that the team effects are not a significant determinant of NHL player compensation. Nevertheless, I proceed with estimation of the model when including the time-varying team characteristics and observe if team effects vanish completely.

5.2 Introducing Time-Varying Team Characteristics to the Model

Returning to Table 4, we can look at the results of Regression 2. This includes the time-varying team characteristics. Fittingly, the coefficients on player performance do not change either in magnitude or significance. Their interpretation is the same as in the first regression. If we look at the coefficients on team characteristics, few are actually significant. The three showing significance are attendance, winning the Stanley Cup this year, and consistent success. Increases in average attendance of 1,000 (roughly 40,000 a season) lead to 2% higher salaries. The positive coefficient on winning the championship can suggest that players have bonus incentives included into their contract, as is often the case, or that teams may be willing to slightly overpay good players to build a championship.

We must be careful when interpreting the returns to historical team success. The introduction of this index was to determine if consistently successful teams were able to attract players at a discount or whether players would be able to extract rent from success. The interpretation of this coefficient by itself is not representative of anything, it should be taken together with the different values associated with the index, as shown in Table 8. The overall result is that players starting the season on a successful team are paid a premium, conditional on the relative success of the team. Since successful teams are most likely to see a financial success as well, one would expect players to received monetary rewards for contributing to the team's success, or for a new player being able to extract some of those returns. Although the impact is small, it is statistically significant. The magnitude may be attributable to the presence of a potential discount, but one that is overshadowed by the aforementioned returns.[9]

Before moving on to team effects I should note the changes in player effects as displayed in Table 5. The variance in those player effects is reduced when I include observable team characteristics to the model. The 'Top 10' table is not displayed but I should mention that of the top 10 player effects, John Madden drops out of the list and is replaced by Nicklas Lidstrom (with fellow Swedes Mats Sundin at 11th and Peter Forsberg ranking 1st). As for the bottom 10 players, the list is identical with a few changes in ranks. The breakdown of fixed effects, as shown in Table 7, remains identical with a slight drop in the statistical

[9] I have run a model where, instead of using H_{jt}, I used a *5 year historical count* variable for each playoff round reached. The results were average positive coefficients (negative for *finals*) and all statistically insignificant on their own. The results presented are of H as it is a total cumulative measure.

significance of height.

Turning again to the estimated fixed team effects in Table 9, the results are interesting to say the least. The estimates now spans a 60% range (standard deviation of 12.7%), up from 40%. Teams paying above a league average are now above by 28% (New York Rangers), while other teams are underpaying their players by 32% (Detroit). It would appear in this case that when controlling for a set of team characteristics, the influence of unobservable team effects is magnified. In fact, the variance is larger and three teams now have a statistically significant fixed effect: Detroit (-32.5%), New Jersey (-25.0%) and New York Rangers (28.6%) with Colorado (-25.5%), barely missing the pack (*s.e.* 0.1819, *p*-value 0.145).

The interesting part here is when we look at those results in conjunction with Table 12. The table is ordered in terms of average historical success over the sample. What we see is that the three most successful teams are also those with the lowest and most statistically significant team effects. Furthermore, I have included the average returning rates for players. These consist of the percentage of players still on the team the following season, and after five years, as averaged over the ten seasons from 1993/94 - 2003/04. All three teams, Colorado to a lesser extent, have a significant returning rate and more so, players stay on the team for a considerable period of time[10]. What this can be interpreted as is that players are willing to take a discount to play on a winning team, and more often will do so to stay on a consistently successful team, resulting in the building of pseudo-dynasties[11] at discount.

One question that arises after observing only three statistically significant team effects is as follows: what kind of players are willing to take these discounts, or demand to be paid a premium? We might expect older players to want to win before retiring, or younger players wanting to get championship experience and potentially earn more in the future. To investigate this, I define three age groups: newcomers, younger than 25 years old; veterans, older than 35 years old; and players in their prime between 25 and 35 year of age. I have

[10]The 2003/04 Detroit team had 17% of its players returning from its 1993/94 team

[11]Dynasties having the understood definition of a team winning 4 or more championships within a decades' time span

interacted these age groups with indicators for the three teams with statistically significant team effects, and displayed in Table 13. What I conclude from these is that older players on the Rangers are the ones receiving a premium while it is the younger players for New Jersey and prime-players for Detroit who earn less. For New Jersey, the interpretation can simply be that the team pays its younger (and possibly more restricted) players less than the rest of the league. As for Detroit, it seems that players in their prime, who can usually extract the most compensation for their skills, are the ones earning less, more evidence that it is the player's choice to earn less to be on this team.

Now, consider the decomposition of ψ_j into various time-invariant characteristics as presented in Table 14. All components are statistically significant, even though R^2 is rather low. When I control for time varying team characteristics, some of the coefficients change in sign, magnitude or significance. A bigger population base can seem enticing for players as there are various activities and opportunities within the team's home town, players may be willing to play in such a market because of those characteristics. The indicator on Canadian teams can have two interpretations; first, one can think of Canadian teams being poorer (as was considered the case during that period, given the low value of the Canadian dollar), but on the other hand one might think of players wanting to play where their sport matters and there is no place in the world where hockey matters as much as in Canada (well, maybe Sweden!) and players would consider taking a 1.5-3% discount to play in Canada.

The Original Six franchises are so called because for a span of nearly 30 years, only those six teams formed the NHL and they have established traditions and community anchorage. The six teams are the Montreal Canadiens, Toronto Maple Leafs, Detroit Red Wings, Chicago Blackhawks, Boston Bruins, and New York Rangers. One might expect to see players taking a discount to play in those markets much in the same way as Canadian markets. What I actually notice is, after controlling for team characteristics, a player could expect to earn 7% above value on an Original Six franchise, possibly extracting rents from those popular markets.

The non-traditional market indicator is based on the so-called 'Southern Belt' teams;

markets in which the presence of naturally occurring ice is scarce or non-existent. Teams in this group include: Atlanta, Carolina, Florida and Tampa Bay in the east and Columbus, Nashville, St. Louis and the entire pacific division (Anaheim, Dallas, L.A., Phoenix and San Jose) in the west. One might expect teams to pay more money to attract players where their sport does not matter. But one could also consider that nice and warm winter climate may attract some players. What I observe is that for those southern teams, players are often overpaid (or possibly compensated) by nearly 10%.

The result for western conference teams is interesting. The major difference between the two conferences is the traveling schedule. Eastern-based teams are all in the same time zone and are close to each other in their own division. Western-based teams actually range from the central region to the Pacific coast. The general reasoning is that players would be less willing to play for a western team given those circumstances, therefore I would expect a positive coefficient. But what I see is teams frequently underpaying for players by more than 5%. This leads us to suggest that players may simply prefer playing in the west despite the traveling disadvantage. But in fact, the reason could lie in marginal revenue. Many western teams are non-traditional markets and the average fan base may be significantly smaller than eastern teams for a similar population base. A lower fan base suggests that potential revenue are lower and the marginal revenue of signing a player are lower. One easy example to consider is the case of New York versus Los Angeles. For a relatively similar population base, the fan base for Los Angeles is smaller and signing a household name would not have the same impact on attendance and revenue as it would in New York. To summarize, this would suggest that the average fan base is smaller in the western conference. If one could get accurate estimates of the fan base, this could be controlled for.

Table 15 presents the correlation coefficients after controlling for time-varying team characteristics. The results are similar to those of the baseline model correlations with two differences. The first one is the smaller correlation coefficient between observed and unobserved player effects. This is most likely attributable to the team characteristics included in the x-vector as it now contains player performance and team characteristics. The second difference is the higher coefficients associated with team effects. In fact, when including team characteristics in the regression vector, the correlation between ψ_j and $x\beta$ goes from 0 to -.09, this would suggest a negative correlation between observable and unobservable team characteristics.

As with the baseline model, I close my analysis of the full model with a look at the decomposition of variance. When controlling for team characteristics, performance *and* team characteristics attribute a lesser proportion of 64% to the variance in log compensation. The proportion attributed to the player fixed effect is up to 29%, capturing the loss attributed to including team characteristics in the regressors. The minor proportion attributed to the team effect in the baseline does go down by nearly half, as I would expect, to end at 0.4%.

6 Conclusion

What I have done in this paper is use the structure of the NHL and the public information available to estimate a fixed player and team effects model to determine if there was a persistent difference across teams in player compensation. What I have found is that when controlling only for a player's performance and experience, there was no statistical evidence of such team effects. What is surprising is that when also controlling for time-varying team characteristics, I do observe some teams paying systematically different than the league average. Though in the end I still found no proportion of variance in log real compensation attributable to these team effects.

Despite rejecting the concept of systematic differences across teams in player compensation, I was able to show that there are some teams paying salaries significantly different from the rest of the league. These teams are Detroit and New Jersey paying below the league average while the New York Rangers are at the top of the list paying well above. The result become more interesting when looking at those teams individually, their success and market conditions depict a sensible picture of these rates. New York is the biggest market in North America, as such I could expect their marginal revenue product to be significantly higher. But even when controlling for potential and realized revenue, I still observe a significant premium being paid. I believe this is simply due to a combination of the team's inability to accurately predict marginal revenue and the ability of players to extract potential rents when negotiating contracts.

As for the other three teams, all one has to do is look at the teams' successes within the relevant timeframe. During the ten years spanning the 1993/94-2003/04 seasons (accounting for success prior to the range of the data), the three most successful teams have been Detroit (3 cups, 1 final), New Jersey (3 cups, 1 final) and Colorado (2 cups - barely statistically insignificant). To make things more interesting, Detroit's loss was to New Jersey and New Jersey's loss was to Colorado. The only other team to appear in the final more than once was Dallas, winning in 1998/99 and losing to New Jersey in 1999/2000. These three teams share 50% of all finalists spots. Even though I control for historical success, I did not observe a significant discount due to success. But what these three teams seem to offer is a consistent chance of winning year after year and being part of a championship team. This is what some owners and mangers like to call a Stanley Cup discount. Furthermore, these three teams have had high player returning rates during their championship runs, as compared to the league in general. Even the 2008 Detroit team had five players from their first championship team in 1998. These teams appeared to offer more than just a chance at a championship, they seemed to be building towards dynasties, offering their players a unique opportunity in their career, signing them at a *dynasty discount*.

I have considered a breakdown of these team effects by age groups with the results being that New Jersey's youngsters are the ones being paid less while it is the majority of the Detroit player in their prime who are paid below league average. This removes some of the dynasty magic from New Jersey as these players are often restricted and may simply be penalized for it. As for Detroit, it suggests something special as these players would be unrestricted free agents and able to negotiate with other teams and be paid at fair value, yet they still appear to be underpaid. One major consideration that could reduce the importance, or magnitude, of this dynasty discount is endorsement deals. Endorsements are a significant source of income for players, and championship members will often be sought after by companies to sign lucrative endorsement deals. This could explain why players on successful teams are willing to take a pay cut, they might actually get compensated through this other form of compensation. I still believe that, even when controlling for other sources of income, this *dynasty discount* would still exist in the case of the Detroit Red Wings.

A Tables

Table 1: Descriptive Statistics for Players

Player Characteristics	Forwards		Defensemen	
Observations	1838		962	
	Mean	St.Dev	Mean	St.Dev
Salary (2003$)	1,867,872	1,961,396	1,778,513	1,482,610
Age	29.4	3.991	29.6	4.082
Experience	7.9	3.922	8	4.21
Games	68.2	13.506	66.7	13.541
Average Time on Ice (min)	15:07	4:11	19:55	4:01
Goals per game	0.202	0.132	0.068	0.058
Assists per game	0.285	0.177	0.212	0.136
Penalty Minutes per game	0.821	0.689	0.894	0.524
Blocks per game	0.231	0.236	0.811	0.703
Hits per game	0.748	0.766	1.07	1.037
Season +/-	-0.203	11.441	1.505	12.735
Career Trophies	0.156	0.977	0.085	0.546
Height (in.)	72.77	2.03	73.92	1.81
Weight (lbs)	202.42	16.23	210.36	13.66
European	0.28	0.45	0.33	0.47
Quebec-born	0.1	0.3	0.09	0.28

Table 2: Descriptive Statistics for Teams

Team Characteristics	Mean	St.Dev
Regular Season Record	53%	10%
Historical Success Rate	15.6%	15.3%
Average attendance	16,583	2,253
Seating capacity	18,451	1,252
Luxury Suites	91	43
Club Seats	2222	1198
Fan Cost Index (FCI)	250.209	42.1207
Population base	4,350,357	3,841,431
Total Revenue	69,600,000	19,600,000
Other Expenses	28,600,000	7,447,857
Market income tax rate	43.5%	5.2%

Table 3: Structure of the Historical Success Rate

Round	Index Value (p)	Increase
Stanley Cup Win	20	6
Cup finalist	14	5
Conference Final finalist	9	4
2nd round exit	5	3
1st round exit	2	2
No berth	0	–

Table 4: Coefficients, Equation (1)

Variable	Baseline Model Regression 1		Full Model Regression 2	
	Forwards	Defensemen	Forwards	Defensemen
Goals per game	0.516***	−0.006	0.527***	0.005
Assists per game	0.416***	0.503**	0.416***	0.492**
PIM per game	−0.005	0.028	−0.001	0.034
Blocks per game	−0.190***	−0.132***	−0.180***	−0.132***
Hits per game	−0.075***	−0.018	−0.073***	−0.014
Games	−0.001	0.002*	−0.001	0.002*
TOI per game	0.030***	0.027***	0.029***	0.028***
Plus/Minus	−0.002	−0.002*	−0.001	−0.002*
Experience	0.311**		0.289*	
Experience^2	−0.008***		−0.008***	
Trophies	0.425***		0.441***	
Trophies^2	−0.038***		−0.040***	
year=2001	−0.093		−0.069	
year=2002	−0.134		−0.043	
year=2003	−0.194		−0.094	
year=2004	−0.437		−0.302	
ln Other Expenses			−0.143	
ln Total Revenue			−0.096	
ln FCI			0.066	
Average attendance (000's)			0.018*	
Tax rate			0.002	
I: Recent team			0.089	
I: Conf. final			0.045	
I: Final			−0.004	
I: Champion			0.106**	
Previous year record			−0.086	
Historical Succes rate			0.004**	
cons	12.023***		15.542***	
N	2327		2286	
R^2	0.925		0.925	

Robust standard errors

* $p < 0.1$ ** $p < 0.05$*** $p < 0.01$

Table 5: Distribution of Estimated Fixed Effects

		Mean	St.Dev	Min	Max
Baseline	θ_i	0.000	0.5983708	-2.372644	1.739366
	ψ_j	0.000	0.0912752	-0.1910969	0.1763317
Full	θ_i	(0.000)	0.5467141	-2.128431	1.695066
	ψ_j	0.000	0.1372706	-0.3251347	0.2858756

Table 6: Extremities Player Effects

Highest 10		Lowest 10	
θ_i	Player	θ_i	Player
1.739	Marian Gaborik	-2.373	Guy Carbonneau
1.729	Peter Forsberg	-2.322	Stephen Leach
1.475	Brad Richards	-2.225	Ed Olczyk
1.457	Milan Hedjuk	-2.140	Grant Ledyard
1.454	Chris Drury	-2.023	Bobby Dollas
1.443	Brian Rafalski	-1.978	Ron Sutter
1.320	Alexei Yashin	-1.973	Rob Zettler
1.315	Simon Gagne	-1.834	Chris Joseph
1.280	Boyd Devreaux	-1.807	Mike Stapleton
1.189	John Madden	-1.785	Dave Lowry

Table 7: Player Fixed Effects Regression, Equation (2)

	ψ_j	Baseline Model	Full Model
Forwards	DM: Height	0.0253**	0.0202*
	DM: Weight	0.0019	0.0017
	I: EURO	0.2484***	0.3159***
	I: QUE	−0.0315	−0.0237
	I: Forward	0.0182	0.0565*
Defensemen	DM: Height	0.0323***	0.0209
	DM: Weight	0.0052**	0.0050**
	I: EURO	0.3074***	0.2692***
	I: QUE	−0.3414***	−0.3158***
	_cons	−0.1005***	−0.1170***
	R^2	0.1077	0.1048

Robust standard errors

* $p < 0.1$ ** $p < 0.05$*** $p < 0.01$

Table 8: Coefficients of the Historical Success Rate

Round	Acievement Level	Coefficient Total Value	Marginal Achievement	Coefficient Marginal Value
Stanley Cup Win	20	8.0%	6	2.4%
Cup finalist	14	5.6%	5	2.0%
Conference Final finalist	9	3.6%	4	1.6%
2nd round exit	5	2.0%	3	1.2%
1st round exit	2	0.8%	2	0.8%
No berth	0	0.0%		

Table 9: Team Effects

Variable	Baseline Model	Full Model
Anaheim	0.134	0.144
Atlanta	−0.044	−0.042
Boston	0.076	0.207
Buffalo	0.004	−0.060
Calgary	−0.024	0.012
Carolina	0.009	0.084
Chicago	0.059	0.145
Columbus	0.053	−0.015
Colorado	−0.140	−0.264
Dallas	0.137	0.067
Detroit	−0.191	−0.325*
Edmonton	0.048	−0.064
Florida	0.003	0.100
Los Angeles	−0.012	0.052
Minnesota	0.007	−0.124
Montreal	−0.068	−0.087
Nashville	−0.027	−0.041
New Jersey	−0.097	−0.250*
New York Islanders	−0.021	0.045
New York Rangers	0.176	0.285*
Ottawa	−0.054	−0.038
Philadelphia	0.073	0.047
Phoenix	0.011	0.022
Pittsburgh	−0.181	−0.214
San Jose	−0.090	−0.081
St. Louis	0.073	0.030
Tampa Bay	−0.037	0.061
Toronto	−0.118	−0.112
Vancouver	0.054	0.087
Washington	0.139	0.146
μ_ψ	0.000	0.000
σ_ψ	0.091	0.127

Robust standard errors

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 10: Correlation Table from Regression 1

	$\ln y_{it}$	$x\beta$	θ_i	ψ_j	$x\beta+\theta_i$	e_{it}
$\ln y_{it}$	1.000					
$x\beta$	0.7066*	1.000				
θ_i	0.3224*	−0.4262*	1.000			
ψ_j	0.0326*	0.0096	−0.0985*	1.000		
$x\beta+\theta_i$	0.9544*	0.7003*	0.3473*	−0.0615*	1.000	
e_{it}	0.2744*	0.000	0.000	0.000	0.000	1.000

* $p < 0.1$

Table 11: Decomposition of Variance of Log Compensation

Proportion of variance of log real compensation attributed to:	Baseline Model	Full Model
Returns to time-varying characteristics ($x\beta$)	0.673	0.635
Player effects (θ)	0.245	0.286
Team effects (ψ)	0.007	0.004
Residual (e)	0.075	0.075
Total	1.000	1.000

Table 12: Associated Success, Fixed Effects and Return Rates

Team	Average H_{jt}	Rank of ψ_j	Average player return rate after 1 year	after 5 years
DET	55	1	74 %	39 %
COL	45	2	61 %	19 %
NJD	39	3	70 %	28 %
DAL	39	22	64 %	25 %
BUF	27	10	71 %	16 %
PHI	27	19	55 %	14 %
PIT	22	4	48 %	8 %
STL	21	17	55 %	11 %
TOR	20	6	58 %	10 %
WAS	17	28	66 %	23 %
NYR	13	30	51 %	11 %
OTT	13	13	60 %	15 %
EDM	12	9	59 %	13 %
SJS	12	8	67 %	14 %
FLO	10	25	63 %	11 %
BOS	9	29	58 %	13 %
CHI	8	27	59 %	10 %
MIN	8	5	66 %	– % †
MTL	8	7	61 %	19 %
PHO	8	16	56 %	10 %
ANA	7	26	54 %	10 %
CAR	7	23	65 %	12 %
VAN	7	24	62 %	9 %
LAK	6	20	56 %	14 %
CAL	2	15	56 %	5 %
TAM	2	21	52 %	5 %
NYI	1	18	54 %	7 %
ATL	-	11	58 %	– % †
CLB	-	14	59 %	– % †
NAS	-	12	60 %	12 %

† Joined the league less than 5 years before 2004

Table 13: Team Effects - Age Interactions

Variable		Full Model
	Anaheim	0.127
	Atlanta	−0.045
	Boston	0.200
	Buffalo	−0.050
	Calgary	0.011
	Carolina	0.075
	Chicago	0.155
	Columbus	0.002
	Colorado	−0.249
	Dallas	0.109
	Edmonton	−0.035
	Florida	0.088
	Los angeles	0.079
	Minnesota	−0.105
	Montreal	−0.068
	Nashville	−0.031
	New York Islanders	0.057
	Ottawa	−0.037
	Philadelphia	0.059
	Phoenix	0.033
	Pittsburgh	−0.195
	San Jose	−0.062
	St. Louis	0.053
	Tampa Bay	0.052
	Toronto	−0.096
	Vancouver	0.100
	Washington	0.162
< 25	Detroit	−0.410
	New Jersey	−1.095***
	New York Rangers	0.303
$\geq 25; < 35$	Detroit	−0.543**
	New Jersey	−0.205
	New York Rangers	0.282*
≥ 35	Detroit	−0.114
	New Jersey	−0.117
	New York Rangers	0.423*

Robust standard errors

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 14: Team Fixed Effects Regression

ψ_j	Baseline Model	Full Model
ln Population Base	-0.0069^{***}	-0.0146^{***}
I: Canadian Market	-0.0292^{***}	-0.0148^{*}
I: Original Six	0.0042	0.0700^{***}
I: Non Traditional	0.0242^{***}	0.0993^{***}
I: Western Conference	0.0049	-0.0548^{***}
_cons	0.0951^{***}	0.1899^{***}
R^2	0.0424	0.1166

Robust standard errors

* $p < 0.1$ ** $p < 0.05$*** $p < 0.01$

Table 15: Correlation Table from Regression 2

	$\ln y_{it}$	$x\beta^1$	θ_i	ψ_j	$x\beta + \theta_i{}^1$	e_{it}
$\ln y_{it}$	1.000					
$x\beta^1$	0.7218^{*}	1.000				
θ_i	0.4130^{*}	-0.2890^{*}	1.000			
ψ_j	0.011	-0.0882^{*}	-0.0909^{*}	1.000		
$x\beta + \theta_i{}^1$	0.9457^{*}	0.7319^{*}	0.4407^{*}	-0.1574^{*}	1.000	
e_{it}	0.2735^{*}	0.000	0.000	0.000	0.000	1.000

[1] $x\beta \equiv x\beta_1 + z\beta_2$

* $p < 0.1$

References

(1997). *NHL Collective Bargaining Agreement 1997.* National Hockey League, New York.

(2005). *The Merriam-Webster Dictionary.* Merriam-Webster Inc, Springfield, MA, 11 edn.

J. M. Abowd, et al. (2002). 'Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data'.

J. M. Abowd, et al. (2003). 'Are Good Workers Employed by Good Firms? A test of a simple assortative mating model for France and the United States'.

J. M. Abowd, et al. (1999). 'High Wage Workers and High Wage Firms'. *Econometrica* **67**(2):251–333.

M. Andrews, et al. (2008). 'High wage workers and low wage firms: negative assortative matching or limited mobility bias'. *Journal of the Royal Statistical Society, Series A* **171**:673–697.

E. L. Groshen (1991). 'Sources of Intra-Industry Wage Dispersion: How Much Do Employers Matter?'. *The Quarterly Journal of Economics* **106**(3):869–884.

J. P. Haisken-DeNew & M. Vorell (2008). 'Blood Money: Incentives for Violence in NHL Hockey'. *Ruhr Economic Papers* **47**.

J. A. Hausman & W. E. Taylor (1981). 'Panel Data and Unobservable Individual Effects'. *Econometrica* **49**(6):1377–1398.

T. L. Idson (1995). 'Team production efects on earnings'. *Economics Letters* **49**:197–203.

T. L. Idson & L. H. Kahane (2000). 'Team Effects on Compensation: An Application to Salary Determination in the National Hockey League'. *Economic Inquiry* **38**(2):345–357.

T. L. Idson & L. H. Kahane (2004). 'Teammate effects on pay'. *Applied Economics Letters* **11**:731–733.

J. Jones & W. D. Walsh (1988). 'Salary Determination in the National Hockey League: The Effects of Skills, Franchise Characteristics, and Discrimination'. *Industrial and Labor Relations Review* **41**(4):592–604.

L. H. Kahane (2001). 'Team and player effects on NHL player salaries: a hierarchical linear model approach'. *Applied Economics Lettes* **8**:629–632.

L. M. Kahn (1993). 'Free Agency, Long-Term Contracts and Compensation in Major League Baseball: Estimates from Panel Data'. *he Review of Economics and Statistics* **75**(1):157–164.

J. Lambrinos & T. D. Asham (2007). 'Salary Determination in the National Hockey League: Is Arbritaton Efficient?'. *Journal of Sports Economics* **8**(2):192–201.

N. Longley (1995). 'Salary Discrimination in the National Hockey League: Team Effects of Team Location'. *Canadian Public Policy* **21**(4):413–422.

R. C. McLean & M. R. Veall (1992). 'Performance and Salary Differentials in the National Hockey League'. *Canadian Public Policy* **18**(4):470–475.

J. Mincer (1974). *Schooling, Experience, and Earnings*. Columbia University Press: New York.

K. J. Stiroh (2002). 'Playing for Keeps: Pay and Performance in the NBA'.

S. D. Woodcock (2007). 'Match Effects'.

S. D. Woodcock (2008). 'Wage Differentials in the Presence of Unobserved Worker, Firm and Match Heterogeneity'. *Labour Economics* **15**(3):492–514.