

# THE PRICE OF LEADERSHIP

---

A THESIS

Presented to

The Faculty of the Department of Economics and Business

The Colorado College

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Arts  
Economics

By

Sam Rothstein

May, 2017

## **Abstract**

Compensation in professional sports is something that is argued and debated over in fan circles all over the world. Whether a player was paid his or her deserved amount is a question that usually has had an ambiguous answer. In the NHL, team captains are an integral part of the success of their team, but are they being compensated for their extra efforts? Data was collected from all NHL players that played a game between 2011 and 2016 and a quantile regression was run to assess how they are being compensated. The results show that at every salary level a team captain is compensated beyond their statistical impact.

KEYWORDS: (Quantile regression, NHL, Captain, Compensation)

JEL CODES: (J24, Z20, J44)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED  
UNAUTHORIZED AID ON THIS THESIS

---

Signature

To Mom and Dad, thank you.

## TABLE OF CONTENTS

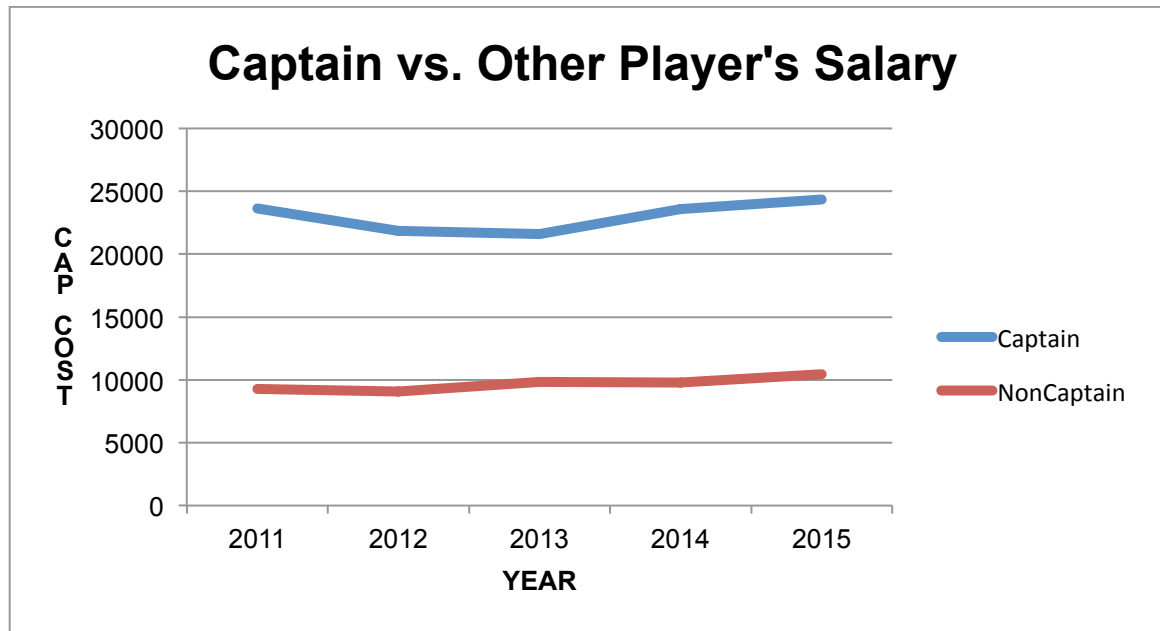
ABSTRACT	ii
1 INTRODUCTION	1
2 Literature Review	3
3 Theory	5
4 Data	7
4.1 Descriptive Statistics.....	7
4.2 Performance Statistics.....	9
5 Results	10
5.1 Quantile Regression Table.....	11
5.2 The Leader's Impact.....	13
6 Conclusion	15
7 References	16
8 Appendix I	18

## **Introduction**

Every year 16 captains lead their respective NHL teams into the playoffs, and at the end of every season only one captain leaves victorious. In what is regarded as one of the most competitive and intense playoff formats in all of professional sports, the captain is the one leading the way for each team throughout the process. In the recent history of the NHL, one of the consistent themes with championship winning teams is a strong leader. The Pittsburgh Penguins and Chicago Blackhawks both appointed new captains in 2007 and 2008 respectively, and have gone on to win 5 of the last 8 Stanley Cups. While there are certainly other important factors within an organization that impact wins, one thing for certain is that players on the team must trust and respect their leader for the team to be successful. By the end of an NHL team's playoff run their injury report is usually populated with everything from broken bones to punctured lungs. The drive for players to sacrifice themselves for the betterment of the team can be attributed in large part to the culture developed by the leadership within the organization (Dirks, 2000). Dedication and trust in a leader is derived through both team success and the leadership skills of a captain (Dirks, 2000). This has made selecting a team captain in the NHL an extremely important move for team general managers and owners.

Considering the importance of the captain's position to the success of NHL teams, I look at how captains specifically fit into an NHL organization. Taking cap cost and statistical data from every player that played a game from 2011-2016 in the NHL, a quantile regression will be used to determine what affects a player's cap cost, and ultimately how a captain is compensated versus the other players on his team. A quantile regression provides specific results for the impact of the independent variables at

different cap cost percentiles. I hypothesize that a player is compensated monetarily for his leadership abilities.



*Figure 1.* Captain vs. Non-Captain Salary. This figure illustrates the mean cap cost of both Captains and Non-captains in the NHL over 2011-2016

After understanding the how a captain is compensated within an organization it is then important to study the effectiveness of captains. By looking at team related statistics I will analyze how a team has improved or declined after a leadership change. Using this method seeks to show that there is a significant improvement within a team's performance after a change from a long-term leader.

## Literature Review

Throughout the history of the NHL there has been substantial research regarding salary determinants for players within the league. Jones and Walsh (1988) and Lavoie and Grenier (1991) were the first to study salary determination within the NHL. They concluded that on ice performance accessed by baseline statistics (goals and assists) was the driving force behind a players' salary. However, they failed to address both the ability of the team (better teams usually have players with better statistics) and the major difference between forwards and defensemen. At the time of the study both papers failed to use anything but penalty minutes as a proxy for a defenseman's ability. In today's NHL game that is not sufficient to identify between an effective and non-effective defenseman. Also, they both concluded that to some extent there is some potential discrimination involved regarding French Canadian born players.

Lavoie, Grenier and Coulombe (1987) and Mclean, Robert C. and Michael R. Veall (1992) used data from the 1990-91 season to conclude that discrimination was present in the NHL. This discrimination takes place when a player is negotiating their first contract in the NHL, and lessens as a player becomes more established. More recently, Bruggink and Williams (2009) studied discrimination and deduced that it is less prevalent later in players' careers, and ultimately may be found outside the realm of wage. This extends to both European and French Canadian players. On top of discrimination there is an issue of unequal distribution of wages within the NHL. Here Marchand, Smeeding, and Torrey (2006) found that each team, and the NHL as a whole, has an unequal distribution of salaries. This distribution places 2/3 of the total league



payroll in the hands of the top third of players. They conclude that players compensated in the top third of the distribution experience a “star effect”. This leads top-end players to play better because they feel their team’s success hinges on their performance.

There are other aspects that need to be accounted for such as whether a player is a free agent. Vincent and Eastman (2012) found that free agency has a negative effect on earnings either when a forward changes teams more than twice, or for a defenseman, more than once. Vincent and Eastman deduced that players actually make more money by staying with the same team their whole career.

Deutscher (2009) is the only paper that assessed the affect of leadership on a players wage (leadership being denoted as a player wearing a “C” on their jersey). While holding everything else constant, Deutscher tested for salary differences between team leaders and other players within the league. He noted that there is a significant wage premium accompanied with the appointment to a leadership position, and that this premium can be from 4%-31%. I go beyond his study by using a multivariate regression approach that includes lagged career statistic values and dummy variables for different positions and fixed effects

## Theory

Given the assumption that teams are going to maximize wins we can assume they are going to assemble a team of players built within the salary cap to best achieve that goal.

NHL organizations operate as monopolies when constructing their teams and allocating resources (contract dollars) under the league agreed upon salary cap. They build their team to the best of their ability by compiling players to fit all facets of the game.

$$\text{Max } \pi = P(Q) \cdot Q - C(Q) \quad (1)$$

Each team maximizes profits ( $\pi$ ) by generating the most possible revenue which is represented by price of one win  $P(Q) \cdot Q$ . That value must be greater than the wages paid out  $C(Q)$ .  $C(Q)$  represents the cost of coaches, GM's, arena costs, and any other fixed cost that would go into running an organization.

$$\text{Max } \pi = P[f(L,K)] f(L,K) - wL - rK \quad (2)$$

Wins are represented by  $Q$ , which can also be denoted as a function of  $L$  and  $K$ . With  $L$  being dollars spent on players salary and  $K$  being money spent by the owner on the team outside of player's salaries.  $wL$  and  $rK$  are used to denote wages paid per game to players, and  $rK$  denotes the amount paid out by the owner outside of player's salaries.

$$\partial \pi / \partial L = P \times [f(L,K)] \times \partial Q / \partial L + Q \times \partial P / \partial Q \times \partial Q / \partial L - w = 0 \quad (3)$$

Each team attempts to find out how valuable each player's salary dollar is in relation to generating wins for the organization.

$$\partial\pi/\partial L = \partial Q/\partial L [P(Q) + Q \partial P/\partial Q] - w = 0 \quad (4)$$

This is a more simplified version of the above equation.

In keeping with Kahane (2001) the compensation model is given by equation (5). The details are in appendix I.

$$Y_{ij} = \beta_0 + \beta_{ij} (X_{ij} - X_{.j}) + \beta x_i + r_{ij} \quad (5)$$

Here  $Y_{ij}$  estimates a specific player's salary (CapCost) on team  $j$ .  $\beta_0$  is a constant and  $\beta_i$  is an unknown parameter for each specific variable  $x_i$ , which include performance statistics and specific player variables.  $X_{ij}$  is player  $i$ 's lagged career points per game, for team  $j$ .

$X_{.j}$  is the average lagged career points per game for all players on team  $j$ . In keeping with Kahane, I use lagged statistics because a player's salary is based off past performance.

On top of lagged values, every player's statistics will be adjusted to per game values.

This gives equal weight to all players regardless of how long they have played. Finally,  $r_{ij}$  is a stochastic error term.

To find the estimates for  $\beta$  we will use a quantile regression. It will test for significance in all independent variables at several different cap cost levels. The regression that will be run is as follows:

$$\begin{aligned} CAPCOSTREALDOLLARS = & \beta_0 + \beta_1 LAGGP + \beta_2 CLAPG + \beta_3 CLGPG + \beta_4 CLTOIPG + \\ & \beta_5 CAPT + \beta_6 DEFDUM + \beta_7 OD2013 + \beta_8 ODNON2013 + \beta_9 SF2013 + \beta_{10} SFNON2013 + \\ & \beta_{11} ENFNON2013 + \beta_{12} ENF2013 + \beta_{13} DUM2011 + \beta_{14} DUM2012 + \beta_{15} DUM2013 + \\ & \beta_{16} DUM2014 + \beta_{17} DUM2015 \end{aligned}$$

## Data

Data was collected from Hockey Abstract<sup>1</sup>. Below is a table of summary statistics for performance statistics used in the study. The rest of the conference and year variables can be found in the appendix.

Table I: Summary Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
CAPCOSTREA~S	3,451	10260.04	8541.23	0	44300.62
LAGGP	3,451	337.2165	287.6568	1	1550
LAGGOALS	3,451	59.29689	83.22768	0	722
LAGASSISTS	3,451	96.93998	123.7433	0	1080
LAGPLUSMINUS	3,451	5.748076	39.88707	-	429
CAPTAIN	3,451	0.0423066	0.2013169	0	1
DEFDUMMY	3,451	0.3454071	0.4755697	0	1
OFFDEFDUM2~3	3,451	0.0095624	0.0973332	0	1
OFFDEFDUMN~3	3,451	0.0257896	0.1585301	0	1
SKILLF~D2013	3,451	0.0228919	0.1495806	0	1
SKILLF~N2013	3,451	0.0501304	0.2182456	0	1
ENFORC~M2013	3,451	0.0107215	0.1030032	0	1
ENFORC~N2013	3,451	0.0292669	0.1685781	0	1

---

<sup>1</sup> The website was <http://www.hockeyabstract.com>. He collected his data via nhl.com

## **Descriptive Statistics**

Descriptive statistics are used to describe player's separate from performance statistics. These descriptive statistics encompass qualities that are usually qualitative (position and whether or not a player is a captain), and can also describe the role a player plays (skilled forward or enforcer). These are important because they can have a serious affect on a player's salary. The dependent variable in this equation (CAPCOSTREALDOLLARS) was calculated by adjusting each player's salary for their yearly cap hit and yearly CPI. The Captain dummy variable (CAPTAIN), and a defenseman dummy variable (DUMDEF) are both descriptive statistics. The next set of dummy variables are set up to identify high offensive output and enforcer behavior for both forwards and defenseman. These variables are assessed during the regular 82 game schedule in the 2011-12 and 2013-16 seasons and separately during the 2012-13 season. In the appendix are the dummy variables that represent season and conference for all players and their teams.

## **Performance Statistics**

Performance statistics are used to separate players by quantitative methods. The statistics used in this study have been around in the NHL for the greater part of its existence. They are important because they denote highly offensive players and also players that are able to play offensive and defensive roles for their team well. Goals (G), assists (A), games played (GP), and plus/minus (PLUSMINUS) are all basic hockey performance statistics. Goals and assists primarily identify highly productive offensive players. Games played and plus/minus are both universal stats to access how much a

player is used in a season, and ultimately how effective he is. Also included are the offensive defenseman dummy, skilled forward, and enforcer variables<sup>2</sup>. These variables capture specific roles played by players within their teams. Included in the study are all players that played a game between 2011 and 2016. The final stipulation is that the player had to have played at least 26 games in one season of his career. Career statistics are gathered for all players who were satisfied these conditions. The statistics are then lagged one year to account for the fact that a player's salary is based off of their past performance. After being lagged the data is then converted to per game values.

---

<sup>2</sup> The offensive defenseman variable denotes a player with over 20 points in the 2012-13 season and over 40 points in 2011-12 or 2013-16 seasons. The skilled forward variable denotes a player with more than 30 points in 2012-13 and 60 points in 2011-12 or 2013-16 seasons. The enforcer variable denotes a player with more than 40 PIMs in 2012-13 and more than 80 PIMs in any of the 2011-12 or 2013-16 seasons.

## Results

After running an ordinary least squares regression I find the captain variable has a positive and statistically significant impact on a player's salary at the 1% level. A WHITE test rejects the null of homoskedasticity, and a Jarque-Bera test rejects the null of normality<sup>3</sup>. A quantile regression approach is employed. This estimator does not require the error term to be homoskedastic or normally distributed. The results of the OLS and the quantile regression are below:

---

<sup>3</sup> The test results can be found in the appendix

Table II: Quantile Regression Results						
TEST	OLS	10%	25%	50%	75%	90%
Variable	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)
CLGPG	8258.853* (6.29)	2212.958* (2.883)	6171.678* (3.1)	14352.66* (5.202)	20146.030* (6.02)	22181.270* (7.186)
LAGGP	7.110* (18.34)	3.162* (6.688)	7.442* (17.464)	9.325* (16.526)	9.204* (9.847)	8.449* (6.301)
CLAPG	3580.711* (3.48)	398.556* (0.407)	4591.210* (3.963)	10547.680* (5.731)	15183.95* (5.532)	19770.810* (7.541)
CLTOIPG	977.031* (25.47)	157.442* (7.391)	172.326* (4.711)	310.953* (5.686)	424.748* (5.9)	448.467* (6.796)
CAPT	2278.093* (6.8)	6945.818 (4.161)	6117.678* (6.98)	3714.091* (5.019)	3008.319* (3.689)	1471.661* (2.952)
DEFDUM	-3101.792* (-9.891)	-393.520* (-2.087)	15.15 (0.048)	219.725 (0.496)	954.524 (1.383)	1875.762* (2.371)
OD2013	4092.704* (4.083)	1188.974* (1.105)	5555.366* (1.998)	7402.836* (4.826)	4939.673* (4.718)	2845.419* (1.987)
ODNON2013	4735.531* (7.592)	2607.525* (1.997)	7722.468* (4.244)	6837.524* (10.225)	5140.179* (6.167)	4777.340* (3.265)
SF2013	4478.928* (6.512)	2604.055* (2.571)	5349.466* (5.353)	4595.405* (3.648)	4433.658* (5.089)	2789.261 (1.69)
SFNON2013	5045.881* (10.704)	4364.264* (4.795)	7114.848* (7.605)	5656.090* (6.864)	3732.122* (4.672)	3125.194* (4.367)
ENFNON2013	2095.349* (3.703)	1109.677* (4.337)	861.179* (2.759)	562.144 (1.397)	357.459 (0.806)	-315.757 (-0.607)
ENF2013	3649.317* (3.871)	1955.941* (5.632)	1675.442* (4.355)	2162.874* (4.255)	1623.396* (2.113)	616.119 (0.706)
*indicates significance at 5% level						



After running the regression using the quantile approach the data behaved as expected. The captain variable was statistically significant at the 5% level at each cap cost increment. Each of the coefficients of the captain variable were positive and relatively large compared to other variables in the regression. The largest coefficients for the captain variable were found in the 10% and 25% cap cost increments. This could be attributed to the fact that a player with a salary within that range would have statistics relatively lower than their peers and thus captaincy has the most significant affect on a player's salary.

The significance of the captaincy can be attributed to the intangible or "extra" things a captain would do daily for his team. These could include; dealing with internal situations, guiding younger players, or helping set the tone and establishing a specific culture in an organization. These abilities have been qualitatively valued in the NHL for years, as is evident by the overall language and hierarchal conditions of the league (Myers, 2012; Rosen, 2010). This study reveals that also quantitative evidence also support the significance of a captain. In summary, both teams and coaches have always lauded the intangible and statistical aspects of being a captain, and now empirical evidence points to these aspects being compensated monetarily.

Beyond just the captain variable the overall model shows a good fit. The R-squared value is around .4 for each of the median, 75%, and 90% quantiles. The lower quantiles, 10% and 25%, both had much lower R-squared value's around .15. The large variation can be attributed to the instability of players at the bottom of the cap cost range. Players in this section of the league are largely unproven or at the end of their career, and thus their statistics are holding less of a bearing on their cap cost. Other intangible

aspects, such as how players fit in within the organization, which can be difficult or impossible to measure, largely impact their cap cost. The overall amount of outside variation can also be attributed to rookie contract restrictions. Rookies have a set cap cost that they can receive each year of their first contract<sup>4</sup>. Beyond the issue of rookie contracts there is also the issue of long-term contracts. Players that are granted long-term contracts (5-10 years) tend to underperform based on their past year's performance, (Bales, 2014; Curry, 2014) which skew data. This happens when a player does not perform up to the value of the contract that person just signed. We account for this by taking a player's career statistics to capture a more realistic picture of a specific player's ability. This dip in performance is most prevalent within the top 25% of scorers within the NHL.

### **The Leader's Impact**

After showing that captaincy in the NHL has a significant impact on a player's salary, the study accesses how the appointment of a captain impacts a team as a whole. Looking at teams that changed their captain between 2011 and 2016, changes in the team performance can be evident. The Detroit Red Wings appointed Niklas Lidstrom to serve as their team captain in the 2006-07 season until the 2012-13 season when Henrik Zetterberg took over. Upon changing captaincy from a defenseman to a forward, the team experienced an increase in goals against per game from 2.48 in 2011-12 to 2.73 in 2012-16. This could also be attributed to a coaching change over the time period, but the main

---

<sup>4</sup> Players younger than 25 years of age as of September 15 during the year of their first NHL contract must sign an entry-level contract, which have set limitations - all entry-level contracts are two-way contracts and the maximum allowable salary for players drafted until 2022 is \$925,000. A player can also receive performance bonuses adding up to their total cap cost of \$3,775,000.

structure of the team was still fairly constant. A similar instance occurred in Ottawa when the team moved captaincy from a forward for 13 years to Erik Karlsson, a defenseman, in 2014-15. The team dropped their goals against per game from 3.23 to 2.62 in one season.

Beyond just looking at teams that changed captains after one player held the position for a while, it is also important to look at teams who have constantly changed leadership. Looking at the Buffalo Sabres and Edmonton Oilers, both of these organizations have had 3 or more captains over the last 6 years. Over that time span both teams have seen their records dip to the bottom of the league standings. The Florida Panthers also cycled through 3 captains in 5 years before landing on Willie Mitchell in 2014-15. He led them to one of their highest finishes in the last 10 years. Mitchell, a defenseman, also aided in a near 20% drop in goals against per game during the 2013-14 and 2014-15 seasons.

Finally, between 2011 and 2016 there were nine captains that were traded between teams. Seven of these players were traded from teams that were non-playoff contenders to teams that were planning on making a deep playoff push. One reason teams trade captains is because the leadership qualities are so valuable selling their services can garner substantial payment (Lane, 2016; Klein, 2014; Johnston, 2013). This is usually the case when a team that is lower in the standings trades their captain for several high round draft picks and potentially some current prospects.

While it may be a reach to assert that team captains are responsible for all of the change in a team's performance, it is important to account for the impact of a captain within an organization.

## **Conclusion**

After testing for significance using a quantile approach, the findings show that being a captain on an NHL team has a significant impact on a player's salary. This study is a detailed account of recent NHL player cap costs and statistics including 3,451 data points over the 2011-2016 seasons. Statistics were gathered from all players that fit the criteria as explained in the data section. The career data for each player was then lagged a single season to represent the fact that players are paid based on past performance. One way to improve this study would be to take data before and after players sign contracts. This would provide specific data with regard to what it takes to earn certain contracts within the NHL, and then how players perform after receiving their new deals. It would also be valuable to incorporate more of the advanced statistics that have been evolving over the last 3-4 years beyond just baseline statistics used in this study. Overall time constraints restricted the use of these methods.

## References

- Bales, J. (2014, August 29). Contract Performance Impact. Retrieved March 06, 2017, from <http://www.rotoworld.com/articles/nfl/48336/71/contract-performance-impact>
- Bruggink, T. H., & Williams, D. (2009). Discrimination against Europeans in the National Hockey League: Are Players Getting Their Fair Pay? *The American Economist*, 54(2), 82-90. doi:10.1177/056943450905400209
- Curry, P., & Drummond, M. (2014, September 18). Top NHL players really do improve in contract year, statistics show. Retrieved March 06, 2017, from [https://www.thestar.com/sports/hockey/2014/09/18/top\\_nhl\\_players\\_really\\_do\\_improve\\_in\\_contract\\_year\\_statistics\\_show.html](https://www.thestar.com/sports/hockey/2014/09/18/top_nhl_players_really_do_improve_in_contract_year_statistics_show.html)
- Deutscher, C. (2009). The Payoff to Leadership in Teams. *Journal of Sports Economics*, 10(4), 429-438. doi:10.1177/1527002509334228
- Grenier, G., & Lavoie, M. (1991). Discrimination and Salary Determination in The National Hockey League: 1977 and 1978 Compared. *University of Ottawa*.
- Hanniman, T., & Grenier, G. (1992). Salary Determination in the NHL. Retrieved from [https://www.ruor.uottawa.ca/bitstream/10393/24993/1/1992\\_hanniman\\_terry.pdf](https://www.ruor.uottawa.ca/bitstream/10393/24993/1/1992_hanniman_terry.pdf).
- Johnston, C. (2013, March 28). Johnston on NHL: Trading captains rarely pays off. Retrieved March 06, 2017, from <http://www.sportsnet.ca/hockey/nhl/johnston-on-nhl-trading-captains-rarely-pays-off/>
- Jones, J. C., & Walsh, W. D. (1988). Salary Determination in the National Hockey League: The Effects of Skills, Franchise Characteristics, and Discrimination. *ILR Review*, 41(4), 592-604. doi:10.1177/001979398804100408
- Klein, J. Z. (2014, February 03). Trading Captain Isn't a Rarity in the N.H.L., and Usually Isn't a Productive Move. Retrieved March 06, 2017, from [https://www.nytimes.com/2014/02/04/sports/hockey/trading-captain-isnt-a-rarity-in-the-nhl-and-usually-isnt-a-productive-move.html?\\_r=0](https://www.nytimes.com/2014/02/04/sports/hockey/trading-captain-isnt-a-rarity-in-the-nhl-and-usually-isnt-a-productive-move.html?_r=0)
- Lambert, R. (2015, August 14). How rare are elite right-shot defensemen? (Trending Topics). Retrieved March 06, 2017, from <http://sports.yahoo.com/blogs/nhl-puck-daddy/how-rare-are-elite-right-shot-defensemen---trending-topics-142721563.html>
- Lane, J. (2016, February 09). Phaneuf joins list of captains traded over the years. Retrieved March 06, 2017, from <https://www.nhl.com/news/list-of-nhl-team-captains-traded-through-the-years/c-278544548>
- Marchand, J., Smeeding, T., & Torrey, B. B. (2006). Salary Distribution and Performance: Evidence from the National Hockey League. *Department of Economics and Center for Policy Research Maxwell School of Citizenship*.

Mclean, R. C., & Veall, M. R. (1992). Performance and Salary Differentials in the National Hockey League. *Canadian Public Policy / Analyse de Politiques*, 18(4), 470.  
doi:10.2307/3551660

Rosen, D. (2010, January 05). Caps name Alex Ovechkin as new captain. Retrieved March 06, 2017, from <https://www.nhl.com/news/caps-name-alex-ovechkin-as-new-captain/c-512478>

The ABC's of Wearing the C. (2012, January). Retrieved March 06, 2017, from <http://www.usahockeymagazine.com/article/2012-01/abcs-wearing-c>

Vincent, C., & Eastman, B. (2012). Does Player Mobility Lead to Higher Earnings? Evidence from the NHL. *The American Economist*, 57(1), 50-64.

Vollman, R. (n.d.). Retrieved from <http://www.hockeyabstract.com/testimonials>

## Appendix I

Leo Kahane's player compensation model:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - X_{.j}) + r_{ij}$$

where:

$Y_{ij}$  = player  $i$ 's current salary (in US dollars), on team  $j$

$X_{ij}$  = , player  $i$ 's lagged career points per game value, playing on team  $j$

$X_{.j}$  = the average lagged career points per game for all players on team  $j$

$r_{ij}$  = a stochastic error term, and  $r_{ij} \sim N(0, 1/4)$  is assumed

Complete Quantile Regression Results

TEST	OLS	10%	25%	50%	75%	90%
Variable	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient t (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)
CLGPG	8258.853* (6.290)	2212.958* (2.883)	6171.678* (3.100)	14352.66* (5.202)	20146.030* (6.020)	22181.270* (7.186)
LAGGP	7.110* (18.340)	3.162* (6.688)	7.442* (17.464)	9.325* (16.526)	9.204* (9.847)	8.449* (6.301)
CLAPG	3580.711* (3.480)	398.556* (.407)	4591.210* (3.963)	10547.680* (5.731)	15183.95* (5.532)	19770.810* (7.541)
CLTOIPG	977.031* (25.470)	157.442* (7.391)	172.326* (4.711)	310.953* (5.686)	424.748* (5.900)	448.467* (6.796)
CAPT	2278.093* (6.800)	6945.818 (4.161)	6117.678* (6.980)	3714.091* (5.019)	3008.319* (3.689)	1471.661* (2.952)
DEFDUM	-3101.792* (-9.891)	-393.520* (-2.087)	15.150 (0.048)	219.725 (0.496)	954.524 (1.383)	1875.762* (2.371)
OD2013	4092.704* (4.083)	1188.974* (1.105)	5555.366* (1.998)	7402.836* (4.826)	4939.673* (4.718)	2845.419* (1.987)
ODNON2013	4735.531* (7.592)	2607.525* (1.997)	7722.468* (4.244)	6837.524* (10.225)	5140.179* (6.167)	4777.340* (3.265)
SF2013	4478.928* (6.512)	2604.055* (2.571)	5349.466* (5.353)	4595.405* (3.648)	4433.658* (5.089)	2789.261 (1.690)
SFNON2013	5045.881* (10.704)	4364.264* (4.795)	7114.848* (7.605)	5656.090* (6.864)	3732.122* (4.672)	3125.194* (4.367)
ENFNON2013	2095.349* (3.703)	1109.677* (4.337)	861.179* (2.759)	562.144 (1.397)	357.459 (0.806)	-315.757 (-0.607)
ENF2013	3649.317* (3.871)	1955.941* (5.632)	1675.442* (4.355)	2162.874* (4.255)	1623.396* (2.113)	616.119 (0.706)
D2011	-3689.499* (-7.043)	-104.728 (-0.379)	-1382.114* (-3.782)	-3241.666* (-6.139)	-3978.808* (6.894)	-2466.623* (-3.064)
D2012	-4694.355* (-8.462)	-1530.606* (-3.755)	-1841.134* (-4.565)	-4308.906* (-7.381)	-4423.326* (-6.157)	-2437.553* (-3.299)
D2013	-4048.878* (-10.111)	-518.810 (-1.211)	-1499.292* (-3.711)	-3598.751* (-8.711)	2146.154* (5.411)	2624.241* (6.511)



	(-8.523)	(-1.834)	(-4.309)	(-6.948)	(4.875)	(-5.157)
D2014	-4099.867* (-8.056)	-1621.087* (-4.851)	-2239.144* (-5.703)	-3829.877* (7.111)	-3849.231* (-6.003)	-1836.648* (-2.005)
PAC2011	-988.677 (-1.415)	-291.973 (-0.722)	31.772 (0.072)	-545.772 (-0.830)	537.8549 (0.713)	410.328 (0.456)
CEN2011	-334.697 (-0.467)	-132.5921 (-0.345)	-84.873 (-0.181)	-339.012 (-0.587)	-86.45052 (-0.118)	193.632 (0.158)
NWEST201 1	-521.074 (-0.727)	77.894 (.226)	63.848 (0.147)	-526.898 (-0.931)	-608.2433 (-0.931)	-230.240 (-0.243)
SWEST201 1	-2.956 (-0.004)	-80.761 (-0.251)	-168.686 (-0.401)	-72.505 (-0.132)	17.66743 (0.023)	905.295 (0.854)
ALT2011	-395.697 (-0.573)	-787.2436* (-1.995)	-896.665 (-1.510)	-348.495 (-0.519)	867.3648 (1.242)	847.306 (0.865)
PAC2012	-448.556 (-0.608)	-178.508 (-0.248)	325.502 (0.668)	630.627 (1.029)	-516.9421 (-0.729)	-769.372 (-0.680)
CEN2012	-163.279 (-.230)	253..100 (0.479)	-170.980 (-0.364)	601.563 (0.943)	-117.0786 (-0.158)	-1181.347 (-1.341)
NWEST201 2	-216.815 (-0.303)	-222.508 (-0.402)	-299.007 (-0.528)	-157.449 (-0.217)	73.72789 (0.097)	-1184.157 (-1.330)
SEAST2012	-149.192 (-0.207)	-179.074 (-0.312)	-564.532 (-1.281)	-357.952 (-0.553)	249.1422 (0.215)	234.8286 (0.281)
ALT2012	-932.6056 (-1.332)	-453.001 (-0.979)	-1461.017* (-3.051)	-114.945 (-0.189)	-554.3435 (-0.788)	-684.8679 (-0.603)
PAC2013	454.683 (0.752)	593.603 (1.844)	501.066 (.421)	162.716 (0.320)	93.93539 (0.133)	-283.6408 (-0.523)
CEN2013	373.092 (0.6196)	507.656 (1.659)	457.2248 (1.234)	397.364 (0.783)	-391.7516 (-0.455)	1417.666 (1.885)
ALT2013	1057.826 (1.861)	627.717 (2.033)	578.0131 (1.495)	1201.404* (2.228)	829.3121 (1.254)	1191.626 (1.673)
PAC2014	-220.739 (-0.359)	445.593 (1.051)	438.0205 (0.994)	133.911 (0.246)	93.85471 (0.144)	-670.7729 (-0.714)
CEN2014	-186.685 (-0.309)	641.165 (1.491)	-72.70441 (-0.151)	-127.622 (-0.204)	111.2044 (0.179)	-691.2610 (-0.669)
ATL2014	901.3434 (1.542)	267.491 (0.608)	790.0747 (1.919)	911.122 (1.705)	756.7589 (1.214)	455.4515 (0.433)

PAC2015	-3411.671* (-6.017)	-1041.709* (-2.111)	-1226.975* (-2.536)	-2659.779* (-4.136)	-2627.389* (-3.080)	-2033.600* (-3.778)
CEN2015	-3901.150* (-6.959)	-1515.252* (-3.790)	-2398.474* (-5.378)	-4115.838* (-6.710)	-3735.041* (-5.755)	-1918.778* (-2.268)
ALT2015	-2929.114* (-5.423)	-1453.672* (-2.891)	-1220.791* (-3.168)	-3192.452* (-5.778)	-2211.816* (-2.224)	-34.476 (-0.040)
*indicates significance at 5% level						

### White's test for heteroskedasticity

F-statistic	24.04122	Prob. F(18,3432)	0.0000
Obs*R-squared	386.4145	Prob. Chi-Square(18)	0.0000
Scaled explained SS	897.9229	Prob. Chi-Square(18)	0.0000

### Jarque-Bera test and histogram of residuals

