

Hockey's Most Controversial Statistic: An Analysis of the Effectiveness of the Plus-Minus Statistic

Melanie Desroches
Department of Statistics
University of Connecticut

November 1, 2024

Abstract

Here is the abstract.

1 Introduction

Use this section to answer three questions: Why is the topic important/interesting? What has been done on this topic in the literature? What is your contribution?

Within the realm of sports, many different statistics are used to determine how good a player is. This can include points, assists, time played, etc. But is there just one value that can be used to determine the effectiveness of a player? This is an important topic, as fans, coaches, players, and general managers often want to get a better understanding of how an individual is impacting their team. It is one thing to watch the players to determine how good a player is, often referred to as the "eye test" but with so many players, it is hard to quantify this. Enter the plus-minus statistic. Plus-minus is generally calculated by adding all the points scored by their team while they were playing and subtracting by points scored by the opposition while they were playing. The idea is that if a player has a generally positive impact on their team, they will have a highly positive plus-minus. The two main sports where this statistic is used is basketball and ice hockey.

While the plus-minus statistic is a great idea in theory, it does not come without its weaknesses. The biggest drawback to this statistic is its issues with independence. Take ice hockey for example. Many ice hockey players tend to play on "lines", meaning the same three forwards tend to play together and the same two defensemen usually play together. As a result, the performance of one player is highly dependent on the performance of their linemates. In "A Regression-based Adjusted Plus-Minus Statistic for NHL Players" [Macdonald \(2011\)](#), Brian MacDonald provides a perfect example of this with the Henrik and Daniel Sedin, Swedish twins who played together for the Vancouver Canucks. ([Macdonald, 2012](#), Daniel spent 92% of his playing time with Henrik, the highest percentage of any other player combination where both players have played over 700 minutes. Because of this high colinearity between the twins, it is difficult to separate the individual effect that each player has on the net goals scored on the ice.) Many critics of the plus-minus argue that plus-minus is more of a team statistic, since it is heavily influenced by team dynamics rather than individual contributions. Furthermore, numerous confounding variables, such as the quality of the opponent and situational factors, make the calculation less reliable. As a result of these criticisms, alternatives to the plus-minus statistic have been developed, such as Corsi or Fenwick, which is calculated using shot attempts rather than goals.

The goal of this project will be to shed light on this controversial statistic and determine if plus-minus is truly an effective predictor to individual contribution, specifically in the National Hockey League (hereforth referred to as the NHL). Is the plus-minus a good evaluator of offensive and defensive output? Is the plus-minus more reflective of how well a player is doing than how well a player is performing? Are there better alternatives to evaluating individual player contribution? These are the questions that will be answered from this analysis.

The rest of the paper is organized as follows. The data will be presented in [Section 2](#). The methods are described in [Section 3](#). The results are reported in [Section 4](#). A discussion concludes in [Section 5](#).

2 Data

Use this section to describe the data that helps to answer your research questions.

The data used to perform this analysis was collected from Natural Stat Trick and the NHL website. The observations in the data is from all players that played in the National Hockey League from the 2021-2022, 2022-2023, and 2023-2024 seasons. Only players that have played in over 25 games were used in the analysis. This is ensure that the players being evaluated were all of similar caliber and were regular NHL players. The columns of the dataset will be combined from the two data sources. The following is a description of each of the columns in the dataset obtained from the Natural Stat Trick website:

Player - Player name.

Team - Team or teams that the player has played for. Not displayed when filtering for specific teams.

Position - Position or positions that the player has been listed as playing by the NHL.

GP - Games played.

TOI - Total amount of time played.

Corsi - Any shot attempt (goals, shots on net, misses and blocks) outside of the shootout. Referred to as SAT by the NHL.

CF - Count of Corsi for that player's team while that player is on the ice.

CA - Count of Corsi against that player's team while that player is on the ice.

CF% - Percentage of total Corsi while that player is on the ice that are for that player's team. $CF * 100 / (CF + CA)$

Fenwick - any unblocked shot attempt (goals, shots on net and misses) outside of the shootout. Referred to as USAT by the NHL.

FF - Count of Fenwick for that player's team while that player is on the ice.

FA - Count of Fenwick against that player's team while that player is on the ice.

FF% - Percentage of total Fenwick while that player is on the ice that are for that player's team. $FF * 100 / (FF + FA)$

75 Shots - any shot attempt on net (goals and shots on net) outside of the shootout.

76 SF - Count of Shots for that player's team while that player is on the ice.

77 SA - Count of Shots against that player's team while that player is on the ice.

78 SF% - Percentage of total Shots while that player is on the ice that are for that player's

79 team. $SF * 100 / (SF + SA)$

80 Goals - any goal, outside of the shootout.

81 GF - Count of Goals for that player's team while that player is on the ice.

82 GA - Count of Goals against that player's team while that player is on the ice.

83 GF% - Percentage of total Goals while that player is on the ice that are for that player's

84 team. $GF * 100 / (GF + GA)$

85 Scoring Chances - a scoring chance, as originally defined by War-on-Ice

86 SCF - Count of Scoring Chances for that player's team while that player is on the ice.

87 SCA - Count of Scoring Chances against that player's team while that player is on the

88 ice.

89 SCF% - Percentage of total Scoring Chances while that player is on the ice that are for

90 that player's team. $SCF * 100 / (SCF + SCA)$

91 High Danger Scoring Chances - a scoring chance with a score of 3 or higher.

92 HDCF - Count of High Danger Scoring Chances for that player's team while that player

93 is on the ice.

94 HDCA - Count of High Danger Scoring Chances against that player's team while that

95 player is on the ice.

96 HDCF% - Percentage of total High Danger Scoring Chances while that player is on the

97 ice that are for that player's team. $HDCF * 100 / (HDCF + HDCA)$

98 High Danger Goals - goals generated from High Danger Scoring Chances

99 HDGF - Count of Goals off of High Danger Scoring Chances for that player's team while

100 that player is on the ice.

101 HDGA - Count of Goals off of High Danger Scoring Chances against that player's team

while that player is on the ice.

HDGF% - Percentage of High Danger Goals while that player is on the ice that are for that player's team. $HDGF*100/(HDGF+HDGA)$

Medium Danger Scoring Chances - a scoring chance with a score of exactly 2.

MDCF - Count of Medium Danger Scoring Chances for that player's team while that player is on the ice.

MDCA - Count of Medium Danger Scoring Chances against that player's team while that player is on the ice.

MDCF% - Percentage of total Medium Danger Scoring Chances while that player is on the ice that are for that player's team. $MDCF*100/(MDCF+MDCA)$

Medium Danger Goals - goals generated from Medium Danger Scoring Chances

MDGF - Count of Goals off of Medium Danger Scoring Chances for that player's team while that player is on the ice.

MDGA - Count of Goals off of Medium Danger Scoring Chances against that player's team while that player is on the ice.

MDGF% - Percentage of Medium Danger Goals while that player is on the ice that are for that player's team. $MDGF*100/(MDGF+MDGA)$

Low Danger Scoring Chances - a scoring chance with a score of 1 or less. Does not include any attempts from the attacking team's neutral or defensive zone.

LDCF - Count of Low Danger Scoring Chances for that player's team while that player is on the ice.

LDCA - Count of Low Danger Scoring Chances against that player's team while that player is on the ice.

LDCF% - Percentage of total Low Danger Scoring Chances while that player is on the ice that are for that player's team. $LDCF*100/(LDCF+LDCA)$

Low Danger Goals - goals generated from Low Danger Scoring Chances

LDGF - Count of Goals off of Low Danger Scoring Chances for that player's team while

129 that player is on the ice.

130 LDGA - Count of Goals off of Low Danger Scoring Chances against that player's team
131 while that player is on the ice.

132 LDGF% - Percentage of Low Danger Goals while that player is on the ice that are for
133 that player's team. $LDGF * 100 / (LDGF + LDGA)$

134 PDO

135 SH% - Percentage of Shots for that player's team while that player is on the ice that were
136 Goals. $GF * 100 / SF$

137 SV% - Percentage of Shots against that player's team while that player is on the ice that
138 were not Goals. $GA * 100 / SA$

139 PDO - Shooting percentage plus save percentage. $(GF / SF) + (GA / SA)$

140 Starts

141 Off. Zone Starts - Number of shifts for the player that started with an offensive zone
142 faceoff.

143 Neu. Zone Starts - Number of shifts for the player that started with an neutral zone
144 faceoff.

145 Def. Zone Starts - Number of shifts for the player that started with an defensive zone
146 faceoff.

147 On The Fly Starts - Number of shifts for the player that started during play (without a
148 faceoff).

149 Off. Zone Start % - Percentage of starts for the player that were Offensive Zone Starts, ex-
150 cluding Neutral Zone and On The Fly Starts. $Off. Zone Starts * 100 / (Off. Zone Starts + Def. Zone Starts)$

152 Faceoffs

153 Off. Zone Faceoffs - Number of faceoffs in the offensive zone for which the player was on
154 the ice.

155 Neu. Zone Faceoffs - Number of faceoffs in the neutral zone for which the player was on

the ice.

Def. Zone Faceoffs - Number of faceoffs in the defensive zone for which the player was on the ice.

Off. Zone Faceoff % - Percentage of faceoffs in the offensive zone for which the player was on the ice, excluding neutral zone faceoffs. $\text{Off. Zone Faceoffs} * 100 / (\text{Off. Zone Faceoffs} + \text{Def. Zone Faceoffs})$

The goal of this dataset was to provide a broader scope of variables that evaluate a players performance. By introducing more advanced and uncoventional statistics, there are more factors to consider in evaluating a player's effectiveness on the ice.

3 Methods

Use this section to present the methodologies that will generate results by analyzing the data.

The main issue with the data is the violation of independence. This can be seen by creating a confusion matrix of the some of the more basic nhl statistics.

There is a high correlation between different shot related statistics and point related statistics. For example, there is a 0.826371 correlation between Goals and Shots. This makes sense because in order to score a goal, the player needs to shoot first. Correlation analysis can be used to identify the strength and direction of the relationship between various advanced metrics and the plus/minus statistic. This was done by calculating the correlation coefficient between +/- and each metric (like CF%, GF%, SCF%, etc.). The correlation values, ranging from -1 to 1, tell us how closely each metric aligns with the plus/minus. Higher positive correlations (e.g., with GF% and PDO) indicate metrics that vary similarly to plus/minus, suggesting that they may capture overlapping aspects of offensive or defensive performance.

Due to the presence of correlation among variables, ridge regression was performed in

Table 1: Correlation Matrix of Variables

	GP	G	A	P	+/-	P/GP	EVG	EVP	P
GP	1.000000	0.660694	0.742812	0.742844	0.212674	0.542885	0.694755	0.806373	0.475903
G	0.660694	1.000000	0.819358	0.933217	0.234048	0.881798	0.980843	0.926390	0.901738
A	0.742812	0.819358	1.000000	0.970627	0.335785	0.895312	0.800044	0.945635	0.748186
P	0.742844	0.933217	0.970627	1.000000	0.308682	0.931216	0.913072	0.981470	0.847371
+/-	0.212674	0.234048	0.335785	0.308682	1.000000	0.276643	0.235106	0.326182	0.186643
P/GP	0.542885	0.881798	0.895312	0.931216	0.276643	1.000000	0.851663	0.892999	0.832988
EVG	0.694755	0.980843	0.800044	0.913072	0.235106	0.851663	1.000000	0.932690	0.804992
EVP	0.806373	0.926390	0.945635	0.981470	0.326182	0.892999	0.932690	1.000000	0.783327
PPG	0.475903	0.901738	0.748186	0.847371	0.186643	0.832988	0.804992	0.783327	1.000000
PPP	0.526041	0.844470	0.912095	0.926069	0.227844	0.908954	0.778026	0.838735	0.884470
SHG	0.410720	0.439135	0.350123	0.403738	0.180917	0.328880	0.416574	0.408319	0.297062
SHP	0.505980	0.417944	0.430347	0.445126	0.282005	0.340711	0.401315	0.454309	0.285980
OTG	0.442653	0.715858	0.708249	0.744332	0.158837	0.725762	0.689839	0.709961	0.682495
GWG	0.599482	0.922624	0.789043	0.881744	0.296291	0.838393	0.901905	0.868988	0.840720
S	0.826371	0.907769	0.892553	0.940538	0.246253	0.835197	0.904258	0.949149	0.782495
S%	0.246746	0.594148	0.335478	0.459613	0.054788	0.555692	0.598461	0.464550	0.495903
TOI/GP	0.559038	0.415454	0.680776	0.601041	0.238598	0.572602	0.394952	0.591843	0.404992

order to identify how plus/minus can be employed to assess offensive and defensive contribution. It was also used to determine if other advanced metrics Corsi or Fenwick have the same, better, or worse predictive abilities compared to plus-minus. Ridge regression, a form of linear regression, is valuable when dealing with datasets with multicollinearity, where predictor variables have some sort of relationship with one another. This applies to hockey metrics like Corsi, Fenwick, scoring chances, etc. since these stats often interact or overlap in measuring aspects of performance.

Coupled with ridge regression, cross validation was utilized to assess the predictive power of different groups of variables (offensive, defensive, possession-based) on the plus/minus statistic. Cross-validation splits the data into training and testing sets multiple times, computing a model's predictive accuracy each time. In this case, the data was split into five subsets. In each iteration, one subset was kept as the test set and the other four were used to train the ridge regression model. The R-squared value was reported for each iteration to measure how well offensive, defensive, and possession-based metrics (like Corsi and Fenwick)

predict plus/minus.

In order to separate individual contributions to plus/minus from team-level effects, a mixed-effects model was used. Mixed-effects models allow for random effects, capturing variability at the team level, while fixed effects capture individual-level metrics. Individual metrics like CF%, GF%, and others were included that directly measure a player’s on-ice performance. The model considered team-level averages (e.g., TeamMeanGF%), accounting for how a player’s team context might influence their plus/minus.

4 Results

Correlation with Plus/Minus (+/-):

Metrics such as GF%, SF%, PDO, xGF%, and HDGF% show a relatively strong correlation with plus/minus, which aligns with expectations since these metrics also track goal-related contributions.

Cross-Validation Scores:

Offensive/Defensive Combined: Averages around 0.53, indicating that these metrics explain a moderate proportion of the variance in plus/minus. Offensive Only: Cross-validation scores are around 0.63, suggesting that offensive metrics alone are somewhat predictive of plus/minus, reflecting the offensive impact. Defensive Only: With higher scores around 0.71, defensive metrics seem to have a greater influence on the plus/minus, which aligns with the role of plus/minus in capturing defensive contributions. Corsi and Fenwick: Both show very high cross-validation scores, with Fenwick performing slightly better, indicating that these possession-based metrics are strong predictors.

Mixed Effects Model:

The significant coefficients for both GF% and team averages, negative for TeamMeanCF% and positive for TeamMeanGF%, imply that team-level factors substantially impact individual plus/minus scores. This aligns with the idea that plus/minus is both a team and

Table 2: Cross Validation Scores

	Both	Offensive	Defensive
	0.56777061	0.64692431	0.73265605
	0.51687324	0.62667921	0.70862251
	0.49576518	0.62263538	0.69467537
	0.49576518	0.58484799	0.65315835
	0.61054685	0.69145036	0.76239753

individual statistic, as team-level scoring factors are significant predictors.

5 Discussion

What are the main contributions again?

What are the limitations of this study?

What are worth pursuing further in the future?

References

B. Macdonald (2011). “A regression-based adjusted plus-minus statistic for nhl players.”

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