

The Effect of an Elite Scoring Presence on NHL Playoff Success

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Abstract

NHL teams clamor each year to sign high-priced free agents, some of whom are great goal scorers. Even before the advent of free agency, these players were always highly regarded, which is perfectly reasonable. Scoring more goals is one way to win more games. However, the question remains whether possessing such a player significantly improves a team's playoff outlook. To assess this claim, we recorded the leading goal scorer on every NHL playoff team since 1986, the year that the NHL switched to its current playoff format. We also measured the regular season luck and adjusted margin of victory for each team. A series of models were analyzed to determine if elite goal scoring remained useful in predicting playoff wins once luck and margin of victory were accounted for. Our analysis showed that this was not the case. Indeed, luck was also not a significant factor if adjusted margin of victory was present in the model. We therefore concluded that teams looking to maximize their playoff success should focus on their weakness, whether that be offense, defense, or goaltending, as opposed to only trying to improve offense. Consequently, elite goal scoring does not appear to be a sufficient condition for NHL playoff success.

Introduction

Like other major sports leagues, the NHL is based on a very simple premise: score more than the other team, and success awaits. Teams are organized through trades and signings by general managers (GMs). The goal of NHL GMs is to build well-rounded teams that have enough depth to overcome injuries and survive the grueling but rewarding journey to the Stanley Cup. This task has been further complicated in more recent seasons due to league expansions since 1967, increasing the number of teams and league-wide parity (Sports Reference LLC. 2020a). GMs are also held in check by a salary cap, which restricts the amount of money they are permitted to spend on players in a season. They must routinely weigh statistical and monetary information to strike a successful balance. Overpaying for a player can saddle a team for years afterward, since contracts commonly span over multiple seasons. Several studies (Chan et al. 2012; Demers 2015; Gramacy et al. 2013) have tried to quantify whether certain players are appropriately paid given their on-ice performance. One considered players independently of their teammates to get an unbiased representation of their abilities. Another divided them into broad groups and assessed salaries based on average performance within the classification. The merit of these studies is clear: if a GM can locate players that the NHL market has undervalued, they can build a roster much more efficiently.

Objectives

In this study, however, we are not explicitly interested in appropriately assigning salaries to players. Instead, we will examine the following question: given that an NHL team has made the playoffs, how does the presence of an elite goal scorer affect the number of wins the team collects?

Statement of Purpose

The offensive schemes of NHL teams tend to fall into one of two groups: more centralized with one or two great goal-scorers, or a more homogeneous approach where it is much harder to pick out one dominating force. This study will assess of the first of these in a playoff context, perhaps indicating a preferred approach to team structure. GMs may have more incentive to build a team around a player, rather than adopting a more piecemeal strategy.

The results of this study could also trigger additional analyses related to salary. Although the research presented here does not directly deal with monetary figures, it is still a practical component to consider. GMs may well choose to reallocate some money to defensemen or goalies if the payoffs are not high enough from our target group. If the results of this study point toward the shocking conclusion that elite goal scorers are not as valuable as they seem, then some teams may seriously reconsider their strategy. After all, elite goal scorers are faces of franchises, and if it would really be more optimal to adapt a more low-key approach, the NHL team building dynamic would be impacted.

Literature Review

If one considers the list of the most highly paid players in the NHL, many of the same players are also great goal scorers – to the surprise of no one (Sports Reference LLC, 2020b). The intent, after all, is to win the Stanley Cup, and a given team must score more than their opponents to do so. Based on this principle, the interest of this paper is to predict playoff success based on a team's offensive prowess. In particular, the main inquiry is if the presence of a high-scoring player on a team contributes to more playoff wins, even when many other variables are considered. Our analysis will use adjusted goals as a benchmark for comparing teams. This

metric considers context, like lockout-shortened seasons and league-wide scoring trends, to standardize goal scoring over different NHL eras (Sports Reference LLC, n.d.-a). Such a measure reflects the fact that scoring 50 goals in 1982, when league-wide scoring was at its highest in the modern era, was quite a different feat than scoring 50 goals at any other time in NHL history (Sports Reference LLC, n.d.-b). Quantifying the effects of a superstar scorer on playoff success could better assess the value of having such a player on a roster.

One researcher, Demers (2015), was also interested in predicting NHL playoff performance. However, his approach was more holistic, in the sense that he was not particularly interested in offensive effects. In his study, Demers compared eight different predictive strategies and eventually settled on the one that performed the best. He classified the performance of every NHL team from 2008-2014 as over-achieving, under-achieving, or expected, for each playoff round. Demers designated only two teams, the Penguins and Kings, as at least slightly over-achieving in each of the four playoff rounds. In other words, both teams were able to outperform Demers' expectations across all first-round series they played in from 2008-2014, each second round series they played in from 2008-2014, etc. And since only two teams were able to separate themselves even marginally from the pack, Demers concluded that the NHL experiences high levels of parity. He notes nearly every team performed at about what would be expected of them over the seven-year period. In any given year, teams could be expected to perform at levels wildly different from their expectation, but these effects appeared to average out even over the relatively short time considered (Demers 2015).

Teams may also be interested in evaluating performance at a more specific level. One could consider results on a player-by-player basis, as a group of researchers Gramacy et al. (2013) did. They were dissatisfied with the plus/minus statistic, which measures the difference

between goals scored and goals given up when a player is on the ice. In their opinion, plus/minus is too dependent on random chance and teammates to be a good individual measure. Their strategy allowed them to account for the context of a player's situation, as a good team could mask poor players and vice versa. In developing a different measure, they were also able to assess the value of players based on their salary. Interestingly, they found that some high-paid players appeared to have little impact on their team, like Zdeno Chara, and Evgeni Malkin. Others, like Pavel Datsyuk, stood out even once his team was accounted for. They found only about 90 players had a significant effect on their team, either positively or negatively. Consequently, there is not only parity amongst NHL teams; the same concept can be applied to players as well. The group also named "budget" players that their metric labeled as underrated. Teams could use the information the group provided to identify hidden sources of strength or weakness in their lineups (Gramacy et al. 2013).

Players with a knack for goal-scoring are valued for obvious reasons in the NHL. However, according to Chan et al. (2012), there are several other distinct types of players, some of whom also bring immediate value to a team. These researchers were interested in classifying players based on certain attributes, such as points, hits, and shutouts, while also reducing reliance on any one of these statistics. They could then identify which player groupings seemed to provide the most value to their team. The result was the classification of forwards, defensemen, and goalies into categories like "offensive", "defensive", "physical", "elite", etc. They denoted what an average player in one of these groupings looks like from a statistical perspective, as well as how many points such a player usually contributes to a team in the standings. These groups were also found to be differentiable by salary, so an individual type could also be classified as generally overpaid or underpaid. They found that goalies are the most valuable on a per-game

basis, while the defensive forward type provides the best total value out of any classification. Their results also showed that defensemen are generally overpaid. The researchers meant for their results to act as a guide for GMs to evaluate trades, who could then compare the number of points expected to be gained or lost by a given deal (Chan et al. 2012).

These studies all tried their hand at measuring NHL performance, either by studying teams or players (Chan et al. 2012; Demers 2015; Gramacy et al. 2013). They also all used regular season data from these entities to inform their results. However, they all went about this process in quite different ways. Demers (2015) attempted to classify teams' postseason performance based on their regular season statistics. Gramacy et al. (2013) analyzed player impact in a vacuum, independently of teammates, via a modification of the plus/minus statistic. Chan et al. (2012) established several broad player types who tend to exhibit certain characteristics. What all three papers concluded, however, is that few players or teams can do anything to separate themselves from the pack for extended periods of time. Demers (2015) found only two teams who barely did so over the course of seven seasons. Gramacy et al. (2013) found only about 90 players whose performances over four seasons significantly differed from that of an average player. Chan et al. (2012) were only able to make claims about their individual groupings, which average information from dozens of individuals. Consequently, it is paramount that a team exploit any advantage it has to gain an upper hand in such a competitive environment. Accordingly, two of the papers here present a sampling of players who stand out for one reason or another. One (Gramacy et al. 2013) named the players individually, whereas the other (Chan et al. 2012) points towards a position and a style of play, namely defensive forwards, as the most efficient. Both results were explicitly intended to be used by GMs, who make decisions about signing and trading players.

Methodology

The purpose of this research is to quantify the effects of great goal scorers on a team's success. Namely, we are interested in the playoff impact, measured in wins, that such a player provides. This study will simultaneously control for other variables to determine if great goal scorers still have an impact even once other important factors have been considered.

Accordingly, our research question of interest is:

- Given that an NHL team has made the playoffs, how does an elite goal scoring presence affect the number of wins the team collects, once we account for:
 - a. Luck, measured by PDO
 - b. Margin of victory, measured by SRS

Under this question, we will test the following hypotheses:

H_0 : Elite goal scorers have no impact on a team's playoff success once other variables have been considered.

H_A : Elite goal scorers have an impact on a team's playoff success once other variables have been considered.

Population

In this study, each observation will consist of a playoff team and some accompanying statistics, like the team's regular season shooting percentage, for example. We will not need to worry about sampling: we will have access to the population, since there are records of every NHL playoff team. Additionally, this study is only interested in considering playoff teams from the 1987 season onward. This is the first year that the NHL made all series best-of-seven, which

is the current playoff format. Previously, the first round was best-of-five, while the remaining three were best-of-seven. Teams only had to win 15 games to hoist the Stanley Cup. This off-by-one error would unfairly devalue older observations in the population. This modification ensures that the results of the study are more generalizable to present-day NHL. Due to this subsetting, the dataset of interest will only contain 528 observations. Although there were only 21 teams in 1987, compared with 31 today, the analysis should still hold because the same number of teams make the playoffs today, 16, as did in 1987.

Data Collection

The data for this study were gathered from the Hockey-reference.com database. The website compiles accurate data by using sportradar, quoted as “the official stats partner of the NHL”, in the footer of the website’s homepage (Sports Reference LLC. 2021a). For the particular interest of this study, Hockey-Reference provides annual regular season data for each team. Given the restrictions previously described, we will only consider NHL seasons post-1986. There should be no concerns regarding the completeness of the data: no missing data occurs in any of these tables. This may have been a concern in earlier NHL seasons, since data collection was not as robust, but by 1987 strategies were in place to consistently collect the statistics we are interested in.

As far as cleaning the data, a three-step process was required. First, any team data before 1987 was not considered as we have previously described. We also eliminated any team that did not make the playoffs, as clearly an elite goal scorer could not help their team win any playoff games if their team did not make the tourney. Lastly, any statistic that was not considered in our model was consequently removed from our data set. Since these measures had no bearing on our analysis, their presence would only serve to complicate the data. The result is a table where each

row is a unique observation, namely, a team and its regular season performance in a year, in addition to how many playoff games it won.

Variables

The response variable in our study is playoff wins, which is a quantitative value that can either be zero or positive. We will include the following predictors:

- Scoring presence: Quantitative variable which is strictly positive. It measures the adjusted goals recorded by a team's leader in that respective category.
- PDO: Continuous variable meant to measure luck as a percentage, with 100% representing the average. Computed as the sum of save percentage and shooting percentage and is based on the idea that regression towards the mean is inevitable in hockey (Sports Reference LLC. 2021b). Any team with a PDO drastically higher than 100% is said to be experiencing good luck, and vice versa for bad luck.
- SRS: Continuous variable with units of goals that can be negative, positive, or zero. Represents the weighted average margin of victory of a team, which considers not only average margin of victory (difference between goals scored and goals given up, divided by games played) but also strength of schedule, or how good the team's opponents were (Sports Reference LLC. 2021c).

Description of Analysis

To consider the effects of an elite goal scoring presence, we analyzed the results of every playoff team in the NHL since 1987. We used forward selection in a regression context to isolate the effects of elite scoring given our other predictors. In particular, the response variable (Y) in our analysis was denoted to be the number of wins achieved in any playoff year by a given team.

The three previously described predictors, SRS, PDO, and scoring presence, were additional attributes used to differentiate teams. The following is our maximum model, describing the scenario where all the predictors were significant:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + E$$

where X_1 represents the SRS, X_2 represents the PDO, and X_3 represents the scoring presence.

This model is subject to reduction from the forward selection process.

Plan to Analyze

The statistical program Minitab was chosen to run the analysis. To address our research question, we will simply note whether the scoring presence predictor survives the forward selection process and appears in the final model. We can also do so with the other two predictors.

To ensure the conditions of normality, homoskedasticity, linearity, and independence are satisfied, both residual and normal probability plots will be employed. Any outliers, high leverage points, and influential points will also be scrutinized, not only because they will provide interesting information about the teams that produced significant residuals, but also because they may significantly affect the model.

Results

Overview

In this study, we were interested in the analyzing the effects of high-scoring NHL players on the playoff success of their respective teams. In the following sections, we will present some information about the NHL teams we studied, our plan for analysis of these teams, and the results of our study. We restricted our analysis to the seasons after 1986, since this is when the

present-day playoff format was implemented. In addition to scoring presence, we considered the luck of these teams, measured as PDO, and their weighted average margin of victory, measured as SRS. If these other predictors prove to be significant while scoring presence fails to be, we may be able to draw conclusions about the star players that some NHL teams are built around.

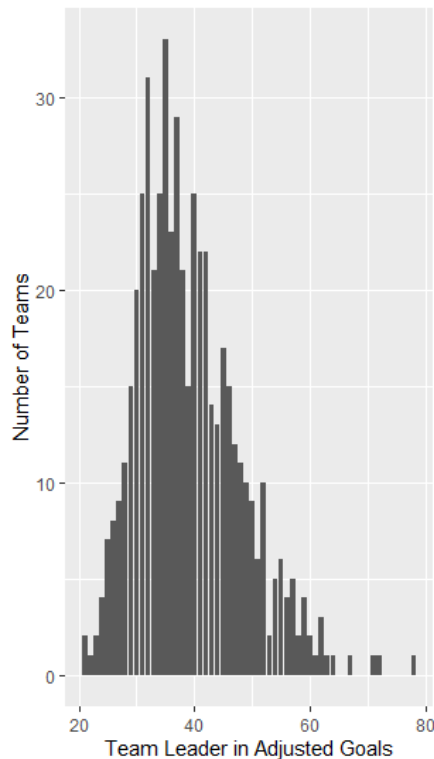
Description of Population

The subjects of this study were the 528 NHL teams who made the playoffs between 1987 and 2020 inclusive. We collected regular season data corresponding to each of these teams, in addition to our response variable, the number of playoff wins. Each year exactly 16 teams made the playoffs. Since we measured data over 33 seasons, we have included 33 teams that won the Stanley Cup. These teams are accordingly labeled with 16 playoff wins. At the other extreme, we coincidentally feature 34 teams that were swept in the first round, recording zero wins during their postseason run. The median number of wins was 3.5, indicating that the typical team lost in the first round. This is absolutely the case, as exactly half of the teams studied failed to the advance past their first opponent.

Figure 1 yields the distribution of adjusted goal leaders. We can see that 35-40 adjusted goals tends to be enough to lead an average NHL playoff team, with every playoff team in our study rostering a player with at least 20 and a handful of exceptions crossing the 60-goal barrier. This illustrates the point that there are only so many goals to go around, especially on teams loaded with talent. It requires an extremely talented player in the right situation, like Brett Hull with the 1991 St. Louis Blues, to post lopsided adjusted numbers, but the statistic generally does well to standardize the given data.

Figure 1

Adjusted Goal Leaders Across Teams

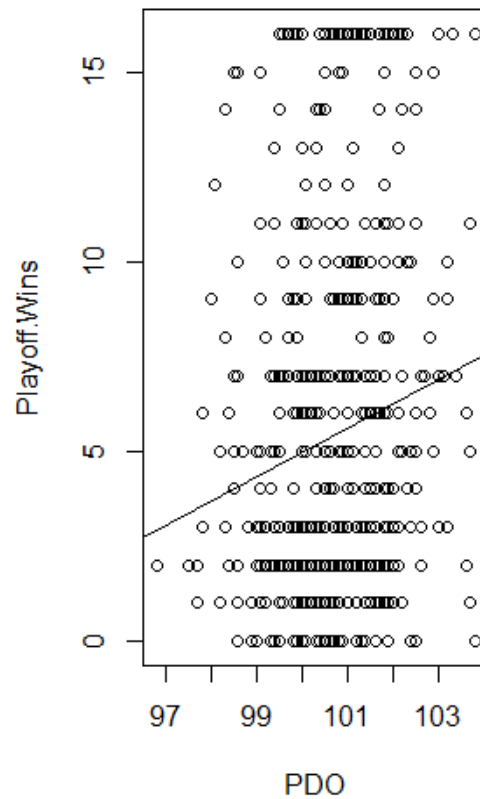


Note. This graph accumulates the number of adjusted goals recorded by the leader in that respective category for every playoff team we studied. This right skewed distribution is indicative of the fact that goal scoring at large in the NHL is right skewed: a few players are exceptionally better, and there is more room above the average than below, so to speak.

Figures 2 and 3 present information about the relationship between the continuous predictors used in the study, SRS and PDO, and the response. Of particular importance is that both relationships appear to be at least slightly positive, with SRS being the more strongly correlated predictor. Supplementally, Table 1 in the Appendix features additional information about the predictors and the response.

Figure 2

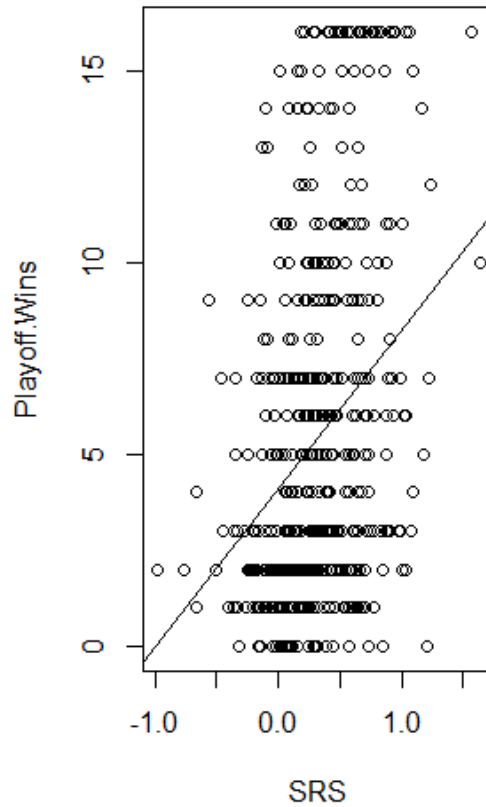
Association between PDO and Playoff Wins



Note. Each data point represents an individual team. The line of best fit illustrates the significant positive linear relationship between PDO, a luck measure, and Playoff Wins ($r=0.165$).

Figure 3

Association between SRS and Playoff Wins



Note. Each data points represents a team. The line of best fit illustrates the significant positive linear relationship between SRS, an adjusted margin of victory, and Playoff Wins ($r=0.311$).

Inferential Results

Our research question revolved around the effect of an elite scoring presence on NHL playoff success. We used the following hypotheses as benchmarks for our analysis:

H_0 : Elite goal scorers have no impact on a team's playoff success once PDO and SRS have been considered.

H_A : Elite goal scorers have an impact on a team's playoff success once PDO and SRS have been considered.

To account for normality issues, we first applied a square root transformation to the response. This cleared up any issues that were present with the normal probability plot and residual histogram. The results of this transformation can be seen in Figures 4 and 5 in the Appendix. At this point, we were able to safely proceed under all the assumptions of linear regression. Upon running the analysis, we first found that although all three predictors were significant in a singleton model, PDO was redundant in a model that already contained SRS ($T=5.96$, $p=0.640$). More importantly, we found that scoring presence was also not significant when SRS was already present in the model ($T=1.26$, $p=0.208$). Tables 2 and 3 formally outlines this process of forward selection. From these results it is clear that although SRS is significant in predicting playoff performance, elite scoring presence is not. We consequently failed to reject H_0 from above.

Table 2

Summary of Singleton Models from Forward Selection

Variable	Coefficient	SE	T	p	95% CI
Constant	1.803	0.058	30.99	<0.001*	(1.69, 1.92)
SRS	0.879	0.125	7.05	<0.001*	(0.64, 1.12)
Constant	-11.850	3.810	-3.11	0.002*	(-19.32, -4.37)
PDO	0.138	0.038	3.66	<0.001*	(0.06, 0.21)
Constant	1.555	0.203	7.76	<0.001*	(1.16, 1.95)
Scoring Presence	0.013	0.005	2.63	0.009	(0.00, 0.02)
Constant	3.920	4.540	0.87	0.387	(-4.99, 12.84)
SRS	0.921	0.155	5.96	<0.001*	(0.62, 1.23)
PDO	-0.212	0.045	-0.47	0.640	(-0.11, 0.07)
Constant	1.568	0.195	8.03	<0.001*	(1.18, 1.95)
SRS	0.844	0.128	6.62	<0.001*	(0.59, 1.10)
Scoring Presence	0.006	0.005	1.26	0.208	(-0.00, 0.02)

Note. This table illustrates forward selection with a minimum p-value for entry into the model of 0.05. Each subsequent pair of lines represents the results of a different model.

* $p < .05$

Table 3 in the Appendix includes information about the 20 outliers produced from our final model. 17 of these observations were teams that failed to win a single playoff game. Due to above average luck, SRS, and scoring presence, the model predicted these teams to perform much better than they did. The remaining three outliers were the opposite case: teams that did not have stats on their side coming into the playoffs but made a “cinderella” run to the Stanley Cup final. The analysis identified no high leverage points or influential observations that significantly impacted the construction of the model.

Although elite scoring proved to be insignificant in our final model, we thought it would be of interest to consider the same analysis as before, but with first round data removed. Perhaps elite scoring may have more of an effect once a team advances deeper in the playoffs. From this we constructed the following hypotheses:

H_0 : Elite goal scorers have no impact on a team’s playoff success after the first round, once PDO and SRS have been considered.

H_A : Elite goal scorers have an impact on a team’s playoff success after the first round, once PDO and SRS have been considered.

Using the same transformation to the response that we applied before, we were able to proceed under the assumptions of linear regression. A forward selection process yielded identical results to the previous analysis, with the singleton model containing SRS representing the only significant addition to a model containing only an intercept ($T=3.41$, $p=0.001$). Table 4 summarizes the outputs from each of these new models.

Table 4

Summary of Singleton Models from Post Hoc Analysis

Variable	Coefficient	SE	T	p	95% CI
Constant	1.763	0.093	18.99	<0.001*	(1.58, 1.95)
SRS	0.601	0.176	3.41	0.001*	(0.25, 0.95)
Constant	-1.580	5.130	-0.31	0.759	(-11.68, 8.53)
PDO	0.036	0.051	0.70	0.486	(-0.06, 0.14)
Constant	1.509	0.278	5.42	<0.001*	(0.961, 2.057)
Scoring Presence	0.012	0.007	1.83	0.069	(0.00, 0.02)

Note. This table illustrates forward selection with a minimum p-value for entry into the model of 0.05. Each subsequent pair of lines represents the results of a different model.

*p<.05

Considering these two results, once SRS and PDO are accounted for, an elite scoring presence does not significantly impact the results of a playoff team, either across the entirety of the playoffs or only after round one. In both cases, the analysis showed that a model containing only SRS is sufficient in predicting playoff wins.

Conclusion

Previously, we failed to reject the null hypothesis that elite scorers have no impact on playoff success. We also considered margin of victory and luck along with elite scoring in our forward selection process. We found that margin of victory alone sufficiently accounts for any variation in playoff success presented by the other two features.

Interpretation

The exclusion of PDO and inclusion of SRS in the final model may undermine the adage that it is better to be lucky than good. There may be some credence to the idea that a team can ride a hot goalie or goal-scorer to the Stanley Cup final, but apparently this does not usually overcome teams that are better overall. A high SRS on its own could indicate at least three things: a high-scoring team with average defense, a low-scoring team with great defense, or a

team that is solid at both. One idea as to why PDO is not as predictively useful is that in two of these situations, a team would feature what is likely to be a top 5 offense or defense. This means that a team could cover for its weakness and overpower any “puck luck” that may historically favor their opponent. The third case simply means that a team is well-rounded, which would indicate that the team is built to perform in the playoffs. There are exceptions, of course. The 2019 Tampa Bay Lightning were identified as an outlier by our final model, and rightfully so: they posted remarkable regular season numbers but failed to win a single playoff game. But generally, our model indicates that luck alone is not enough to overcome great teams.

Many successful teams in our study featured a great goal scorer. With regards to the near-significance of elite scoring in our final model, we will first note the three outliers that the model underestimated. Two of these teams won the Stanley Cup, the 2019 St. Louis Blues and 2012 Los Angeles Kings, and another made it to the Final, the 1991 Minnesota North Stars. Both the Blues and Kings were carried by hot goaltenders who more than made up for poor offensive support. The North Stars were more of a strange case, posting weak all-around regular season numbers, but went on an impressive playoff run in spite of it. Additionally, there were 17 teams with strong individual scorers, like the 2003 Detroit Red Wings and the previously mentioned 2019 Lightning, who failed to win a single playoff game. Situations like these could be explained several ways. These teams may not have saved up enough energy come playoff time, since playoff hockey comes at a different intensity than the regular season. An opposing team may have experienced puck luck on a smaller scale. Although we identified that PDO was not a significant factor across the length of postseason, it is much more likely that it has an impact at the level of individual series, games, and goals. This would be enough to sway momentum towards the other team. There is also likely a psychological aspect as well. The teams that

succeeded may have clutch playoff performers rostered, or those who lost may have had players who folded under pressure.

Implications

Based on our analysis, concentrated goal scoring alone is not sufficient for playoff success, given that the team already sports a high enough SRS. This would indicate that teams should be more focused on either making their team more balanced, or not necessarily focusing on just star offensive players to improve their team. Note that our model does not dissuade signing such players: it just does not recommend doing so above all else, regardless of the team's situation. We would agree that many, if not all, NHL teams generally follow this methodology year in and year out: improve weaknesses before strengths. There may be some exceptions, but this means that we support the conventional wisdom when it comes to team building. It is also quite likely, although not a guarantee, that our results translate to regular season success as well. Since playoff competition is guaranteed to be on average tougher than regular season competition, it seems reasonable to assume that a strategy which consistently works in the playoffs would work in the regular season; the converse appears less likely.

Limitations

Initially, we were interested in measuring elite scoring through an indicator variable in the model. If the team rostered a player who recorded 50 or more adjusted goals during that particular regular season, the variable would equal 1, and otherwise 0. However, this produced very sparse data, as only about 1 in 8 teams met this criterion. This variable condensed the data too much. To fix this, we converted the variable to instead represent the leading adjusted goal scorer on each team. This would in theory show the same general results as the original, but with

more predictive validity as each team was described more accurately. These updated values also proved to be much more difficult to obtain but were certainly worth it.

Future Research

One adjustment to this study that may improve its validity is the usage of point shares as representations of offense, defense, and goaltending in the model, instead of adjusted goals and PDO. Much in the same way that we considered the leader in adjusted goals on each team, one could also instead include the team leader in offensive points shares. This way, defense and goaltending would be more explicit in the model and could be compared to offense much more naturally. Team totals in each of these categories could also be included to address the differences between teams with more concentrated talent and more balanced squads. SRS could likely remain in the model, however, as an overall indicator of team strength.

Another slight modification of this idea would be to consider the offensive point shares contributed by the top line and defensive points shares contributed by the top pairing of defensemen as a percentage of the team's total offensive or defensive point shares, instead of simply the team leader in each of these categories. This may more accurately address the contributions of a team's top players, within the context of the team's overall performance.

Conclusions

The impact of elite scorers on NHL team success is a topic that is not going away any time soon. However, our analysis indicates that their presence on a team does not necessarily indicate a better shot at winning the Stanley Cup. Rather, they are likely just a piece of the puzzle. We encourage teams to continue to use talent acquisition to address their weaknesses,

whatever they may be. An elite goal scorer is unlikely to overcome the issues of a flawed team on their own, unless that problem happens to be lack of offense.

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Appendix

Table 1

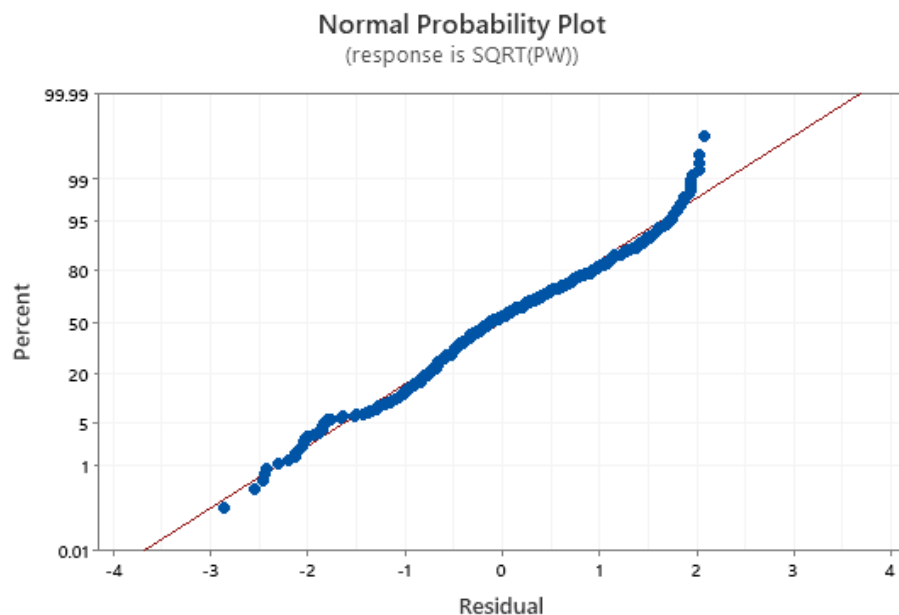
Summary of Select Attributes

Measure	Mean	SD	Five Number Summary				
			Minimum	First Quartile	Median	Third Quartile	Maximum
SRS	0.31	0.35	-0.99	0.08	0.29	0.52	1.64
PDO	100.70	1.18	96.80	99.90	100.60	101.50	103.80
Scoring Presence	38.99	0.33	21.00	32.00	37.00	44.00	78.00
Playoff Wins	5.39	4.61	0.00	2.00	3.50	7.25	16.00

Note. Scoring Presence is the most adjusted goals recorded by a single player on a roster during the corresponding regular season. SRS represents weighted margin of victory, which not only considers average margin of victory but also opponent strength. PDO measures luck, where 100 is average, less than 100 signals bad luck, and greater than 100 signals good luck.

Figure 4

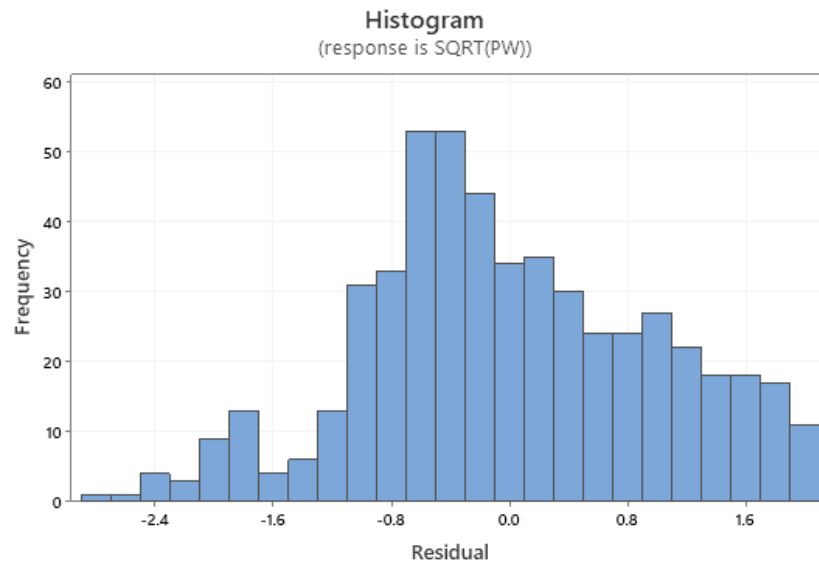
Normal Probability Plot from Final Model



Note. This graph quantifies the adherence of the predictions to a normal distribution. Since many of the plotted values fall on or nearly on the red reference line, we can conclude that the square root transformation applied to the response was successful in addressing the issue with the regression assumption of normality.

Figure 5

Histogram of Residuals from Final Model



Note. The distribution of residuals here is not centered at zero and is skewed to the right.

However, these effects are not significant enough to void our analysis.

Table 3

Outliers from Final Model

Year	Team	SQRT(Wins)	Predicted SQRT(Wins)	Residual
2019	Tampa Bay Lightning	0.000	2.879	-2.866
2003	Detroit Red Wings	0.000	2.550	-2.550
1999	Ottawa Senators	0.000	2.506	-2.444
2001	Ottawa Senators	0.000	2.470	-2.470
1993	Boston Bruins	0.000	2.426	-2.426
1993	Chicago Blackhawks	0.000	2.316	-2.316

2006	New York Rangers	0.000	2.229	-2.229
2000	Florida Panthers	0.000	2.208	-2.208
2018	Los Angeles Kings	0.000	2.166	-2.166
2019	Pittsburgh Penguins	0.000	2.141	-2.141
2017	Chicago Blackhawks	0.000	2.078	-2.078
2000	Los Angeles Kings	0.000	2.073	-2.073
1987	Boston Bruins	0.000	2.027	-2.027
1994	New York Islanders	0.000	2.018	-2.018
1999	Mighty Ducks of Anaheim	0.000	1.993	-1.993
2015	Winnipeg Jets	0.000	1.996	-1.996
2018	Anaheim Ducks	0.000	1.991	-1.991
2019	St. Louis Blues	4.000	2.012	1.988
1991	Minnesota North Stars	3.742	1.710	2.031
2012	Los Angeles Kings	4.000	1.905	2.095

Note. This table lists the teams identified as outliers from the final model containing only SRS.

These entries are organized in ascending order by residual. The last three teams in this table significantly outperformed the model's prediction; all other significantly underperformed.