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DRAFTING DEFENSEMEN'S EFFECT ON NATIONAL HOCKEY LEAGUE OUTCOMES

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Abstract

Any draft in the league's "salary cap era" (2005– Present) would go differently with hindsight & with knowledge of the ultimate realized value of players. This study aimed to explore whether National Hockey League (NHL) teams that choose to draft defensemen in the first and second round of the draft more often will perform better as a team. The study investigated data from 12 seasons 2007-08—2018-19 in the National Hockey League with 30 teams per year. The study incorporated several independent control variables and conducted an OLS regression on defensive draft investments' ability to predict regular season winning percentage. The OLS model was a generally good fit with an adjusted R^2 of .632 (F(15, 344) = 42.04; p<.001). The results indicate that defensemen selected in the draft's first two rounds are responsible for a tangible effect on NHL team outcomes. It was found that the number of *Draft Selections* had a statistically significant relationship with regular-season winning percentage (p=.006) and each additional defenseman drafted in those rounds corresponded to a 0.7% improvement in a team's season winning percentage (p<.001). Additionally, for every standard deviation increase in the use of non-drafted defensemen (free agents or transfer minutes), you would expect to see a reduction in team winning percentage of 4.6% (p=.003). A logit regression was also used to analyze the same variables' ability to predict a playoff berth (Model fit: $\chi^2(15,360) = 205.22$, p<.001). While traditional performance factors of *Offense Quality* and *Goalie Quality* were significant predictors of playoff qualification (p<.001), the defensive draft variables were not significant. Offensively-minded defensemen also did not present a statistically significant effect on winning percentage or playoff berths for NHL clubs in either model.

Introduction

Sport has undoubtedly ensnared our society with its pageantry and unpredictability. “No other activity so paradoxically combines the serious with the frivolous, playfulness with intensity, and the ideological with the structural” (Frey & Eitzen, 1991). At its simplest, sport describes a contest between competitors, and the degree of difficulty or similitude among these competitors is all the more visible in professional sport. Professional sport organizations are granted the annual opportunity to induct these competitors into their team via a draft: a systematic process of distributing new athletes for league teams. Ice hockey is a sport that uses this process (NHL draft rules, n.d.). The defense position in the National Hockey League (NHL) is a valuable type of player that is sought after. The primary factors to team performance – at the simplest level – are Offense, Defense, Goaltending & Opponent Quality. Then, defensemen are not only a big piece of the primary factors but they are partially responsible for executing the flow of a team’s play. Teams in the NHL may aspire to acquire prospective all-star defensemen in the draft since it is very unlikely one would be available on the trade market without a significant expenditure. The purpose of this study is to provide an examination of NHL team performance with respect to drafting defensemen. The defense position has a unique impact on the game since there are typically only 6 of them in a match per team. Furthermore, in the game today, all players on the ice must work together to facilitate offense in the offensive zone, and that includes defensemen (Yli-Junnila, 2019). Therefore, this study will examine both top defensemen and those with some identifiable offensive capability.

Research Questions

The central research questions for this thesis are:

Will there be a positive relationship between allocating draft capital to the defense position and subsequent team performance?

Is there a relationship between the use of drafted offensive-defensemen and team success?

Hypotheses

H1: Controlling for other team performance predictors, using 1st and 2nd round draft selections (draft capital) on defensive players will be positively associated with team performance.

H2: Controlling for other team performance predictors, recent 1st and 2nd round defensive draftee playing minutes will be positively associated with team performance.

H3: Controlling for other team performance predictors, using 1st and 2nd round draft selections on offensively oriented defensive players will be positively associated with team performance.

H0: Defensive player drafting, utilization and offensive orientation will have no relationship to team performance.

Significance

The impact of a single top defenseman is magnified as a result of how few of them typically play in a game per team. In contrast, there are commonly 12 forwards available for a team. In previous eras, the game saw defenseman be more physical and there was an elevated 'toughness' aspect to the game. In an article about fighting and toughness in the NHL, the author writes, "Back when we all played in the seventies, eighties and nineties….it was about hitting, taking hits, fighting, sticking up for your teammates; But that stuff's kind of gone by the wayside" (Duhatschek, 2020). In today's game, there is an incredible emphasis on speed and providing positive value in all three zones: offensive, neutral and defensive (Katsaros, 2022). Therefore, a modern defensemen – at least those who are assigned significant minutes – must possess a multitude of skills. Therefore, since there are typically only two of them on the ice per team during a 'shift' of gameplay, the importance of utilizing the best personnel is amplified. It is possible that offensive bias may undermine draft practice in the NHL; there exists a trend of Canadian Hockey League (CHL) defensemen who score being more often drafted in the first 25 picks (Jessop, 2013). Lastly, there exists a motivation to perform well in drafting defensemen because an NHL team could bring in $1.5 to $3 million for a home game; however, that number can "rise exponentially" for playoff games (Burnside, 2020). Of course, a high regular-season winning percentage correlates directly with the postseason.

Delimitations

Draft information from 2007-08 to 2018-2019 will be examined. These years were chosen as to be exclusively during the league's salary-cap era and all seasons occurring before the COVID-19 pandemic.

Limitations

Limitations include how the study is limited to a certain time frame of which was laid out in the delimitations.

Assumptions

- The data available to the study's author is accurate and reliable.
- The labor market post-draft is relatively fluid and competitive.
- Assume player location preferences don't significantly confound retention and movements.

Operational definitions

- **NHL Salary Cap era**: the period of time in which the NHL has instituted a ceiling of spendable money in hopes of diminishing the gap between the richer and less rich teams, spanning 2005—Present (Peden, 2011).
- ‘Elite’ or ‘Top’ player: A specific player who, statistically, performs at a high percentile relative to his peers.
- Draft capital: A term that quantifies all draft selections that a team holds in a given year in terms of quantity.
- ‘Expansion Draft’: A process whereby a brand-new team is able to select one player at minimum from each existing club in order to field a team. Booth, K. E. C., Chan, T. C. Y., & Shalaby, (2019)
- ‘Corsi’: “A Corsi number is determined by taking the number of shot attempts at even strength and dividing it by the number of shot attempts by the opponent” (Masisak, 2015). To paraphrase, Masisak also writes that Corsi could be a quality predictor of the future.
- ‘Points/60’: This is obtained by calculating (Points*60)/PlayingTime. It takes deployments, type of points and other intangibles into account to produce an all-encompassing stat for regulation time (60 minutes).
- ‘Offensively-minded defenseman’: A player in the defense position who makes an effort to actively contribute offensively. For the purposes of this study, they will be defined by Points/60.

Chapter 2: Literature Review

By the league rules, every team (32) in the NHL is granted one first-round selection per year. They can elect to trade it for a current league player or use it in the draft to choose a new player from the remaining draftable pool of talent. Typically, the "best" – or highest consensus rated – players are taken in the lowest numbers of the draft (i.e., 1st overall, 2nd overall). General managers (GM) have a high number of choices to make based on this system, but this study will focus on selection of defensemen in this process. The literature review for this chapter included search terms in Google Scholar like "NHL wins model" and "NHL Draft." This process also scoured library databases such as SportDiscus to search for topics like "Sport draft economics," "Sport draft bias" and "sunk cost in sport" while excluding results that related to topics like "exercise physiology," "sport genetics," "psychology" and "tanking." There were at least one or two quality results per search after sorting by peer-reviewed academic journals and using these exclusions. Studies that include quantitative modeling were desired, and finding adequate studies also consisted of scrubbing previous studies' reference lists. Studies that focused on goaltenders and their analytics were also not prioritized.

This chapter will present the foundational background topics and the current related research organized in three sections. The first section, 'Hockey Players', outlines what positions a player can play and a general description of their usage. The second section, 'Sports Labor', will explain player mobility, salary caps and the NHL Draft. The final section will review literature related to 'Team Performance,' i.e. outcomes in NHL team regular seasons and playoffs as a result of defensemen.

Hockey Players

Background on Defensive Players

At its core, the defenseman position is obligated to transfer the puck from areas around his own goal to his own players and, in turn, move it towards the other team's goal. From a coaching standpoint, defensemen are also essential in annulling the other team's best players. Overall, a defenseman does not have to be a specialist in offense or defense exclusively, but the player shouldn't be all-around low-quality, either. Existing published writing, much of which is credible but not peer reviewed, suggests that "two-way" defensemen are the type of defenseman that is expected to excel in every facet of the game (Rookie Road, n.d.). Additionally, there are two defensemen on the ice per team for a typical 'shift' of gameplay, and they must be sufficient in assisting or driving play at even-strength & in the offensive zone in order for a team to have the largest chance at producing overall offense (Yli-Junnila, 2019). The reasoning becomes: since there are only two defensemen on the ice for a conventional 'shift' of gameplay, a team would be best served for them to be high quality. The way an average team operates is in pairings. There are first, second and third pairs. Star players are going to live on the first, while the secondary wave is the next best and so on. It is sound reasoning to assert that once a team acquires a defenseman who shows signs of being elite or one who has finally arrived, they are not going to make him available via trade. They may not accept *any* trade proposals, and top defensive players typically don't move at least until they have exhausted their entry-level contract, which typically spans three years (Murphy, 2022). Perhaps the only situation in which a team would exchange such a player would be to flip the value into a different position. As a result, teams must look to the draft for such players. Top defensemen have been drafted high in the past, such as 2017 where the player who was taken fourth overall is among the leaders in points, but not every year has been optimally executed (hockeydb.com, n.d.).

A high-quality hockey team possesses the ability to do the following: when a defenseman cycles closer to the net and "abandons" their natural position area to keep a play going, a forward will cover that area for them. A team will keep this cycle going for as long as potentially necessary to facilitate full puck possession, and a "rover" defenseman – like Kris Letang in the 2016 Stanley Cup Final Game 6 – truly can impact the entire offensive zone for a team. What's more, an ice hockey defenseman is primarily responsible for taking the puck from below his own goal line and moving it the other direction as safely as possible (Jeremy, 2021).

Player Contributions

The work done by Jensen, et al. (2013) is a useful tool that would allow for identifying what kind of impact any specific player has on his team. The authors identify that a metric already exists for player impact, but it only measures the "marginal effect" of players as the authors point out. They utilize a logistic regression model using a Bayesian approach, and after placing a "Laplace prior distribution on player coefficients," they are left with a result that provides a unique look at players. This is highly relevant to the study because it is examining a single position group. However, it must be noted that such research is perhaps an advanced and even later version of analysis; this study aims at acquisitions of defensemen, and Jensen et al. talk about optimal usage of players after they are on a club.

Central Scouting Service

As a result of a lack of literature in National Hockey League scouting, this work was included for thoroughness. Schuckers and Argeris (2015) aimed to predict the return on investment for an NHL team's scouting. The authors compare internal scouting versus using the public work from NHL Central Scouting. The study examines the NHL drafts from 1998 through 2002. Certain metrics such as GVT (goals versus threshold) in the study are similar to baseball's 'wins above replacement' model. Overall, the study's methods are quantitative in illustrating/predicting the first 7 seasons of a player's career's GVT, TOI & GP. So, the authors provide a look at the percent of times that "the ordering by CSS" came as close as possible to the optimal choice in the respective draft, by position Schuckers and Argeris (2015). Then, the authors dive into what they call "rank differential rank." This analysis adheres to the following: player A was taken 6th overall, but the central scouting group had player A ranked 13th; therefore, the 'rank differential' would produce -7. Lastly, plots are provided that accomplish the following: statistical player accomplishments from GVT, TOI & GP relative to expectation. This paper is relevant to the study because it further examines practice of optimal drafting.

NHL player puck shooting

A quantitative look at weighted and predictive data for skaters is presented Macdonald, et al., (2012). It is a study where distance from the net is taken into account for the 'weighted' shots model. The study aims to use "weighted shots and advanced stats based on weighted shots" to list players in the following order: list the top 5 players with the greatest difference between actual goals scored and expected goals scored" MacDonald, et al., (2012). They continue that shots from a forward are weighted higher than that of a defenseman because a defenseman traditionally plays higher near the blueline. However, with the rise of 'offensive-defensemen,' it isn't out of the question for the defense to provide offense; sometimes it is in the form of a low wrist shot on the net. As a result of this, the scatterplots are key in seeing how defensemen fared in this 'weighted' metric. Some defensemen, like Roman Josi, Cale Makar and Victor Hedman, shot over or around 2.5 shots on goal per game in 2021-22 (nhl.com, n.d.). So, as an organization, this study serves a tremendous purpose in analyzing a blueline's shots and can provide a unique grading of defensemen.

Sports Labor

The Sports Labor section will extensively cover works from the drafting, game prediction, sunk cost fallacy and wins-above-replacement categories as the study moves in to examining sport as a labor market.

Strategy for drafting

The National Hockey League (NHL) allows its member organizations to induct a minimum of seven rookie players to their organizations every summer in the entry draft. Over the course of a few days, the league holds an in-person ceremony, beginning with the first round. To be eligible to be drafted, players must be a minimum of 18 years old by Sept. 15 of the draft year and below 20 years old by the ensuing Dec. 31 (Repke, 2013). The quantitative literature stresses a hypothetical strategy of taking the draft's highest-quality remaining player from a team's last pick and repeating this back until a team's top pick, whatever number that may be (Nandakumar, 2017). This is also referred to as 'backwards induction', where a team's decisions are reverse-engineered in order to re-create a fully optimal, single-team draft list. It must be mentioned that while this may be an assumed practice, no examination between offensive-defensive player preferences was undertaken. The study stresses that "backwards best-player available outperforms best-player available" (Nandakumar, 2017). Best-player available refers to selecting a player who does not necessarily fill an organizational need but one that provides organizational value.

How many games will an NHL player play?

In sport, and especially one that operates with a "hard cap," mining the highest possible return-on-investment is certainly momentous. The work done by David R. Wilson (2016) simply aimed to be able to predict which players in a draft will play games – 1 or higher – for the franchise that drafts them. Such a thing is not guaranteed. Examining the figures provided in this study, the actual value available in a given draft including all positions is uncovered. It is indicated that ~20.19% of players drafted in 2006 went on to play 160 or more games in their careers (Wilson, 2016). It bears to reason that the number of valuable and not simply 'replacement level' defensemen is going to be a fractional amount of the original 20.19%. Without going off on a tangent in the realm of how "staying healthy" isn't always easy for a player regardless of value, the author continues with some potentially helpful figures on forecasting a single player's likelihood to play 1 game. Wilson's work is relevant to the study because if the premise is that the draft has been very lucrative in providing valuable defensemen, more work is required in order to find the best ones. This research also points to the importance of examining draft (defensive) player utilization, i.e. minutes played, in addition to the basic draft selections.

Intangibles

Similar to David Wilson's work, Schulte, et al. (2018) provide another way of looking at intangible characteristics of NHL prospects. The reasoning for it is to visualize draft and scouting preparation in a different way; or, as they put it, "weights can be used to identify which features of a highly-ranked player differentiate him the most from others in the group." (Schulte, et al., 2018). From the piece, only one aspect of it will be used. The authors' point/header #8 is intended to offer a 'difference' between high-ranking players on a draft list. It provides a glimpse into the three most important details that landed a player on a draft 'board' or ranking. This is significant as defensemen are available from all over the world & all leagues with varying levels of play.

Optimizing an expansion draft

Both of the following studies reviewed that pertain to optimization of an expansion draft are relevant because of how few works there were in the strategic decision-making angle.

Booth, Chan, & Shalaby (2019) investigated the 'ins and outs' of an NHL expansion draft. They looked at the various trade-offs a team could emerge with such as side-dealing, the financial situation of the franchise post-selections and being 'paid off' to act a certain way in the draft. In addition, there are a pair of "optimization models" that the authors provide. One is used so a team can enhance their player decisions (protect, expose); the other is to automatically compose a brand-new team that is salary cap compliant.

The work done by Farah, L. & Baker, J. (2021) offers a way of measuring how a given forward or defenseman's career will shape out based on draft selection number. It then provides a look at the position by round. This of course is important because it could show us each draft's profitability in terms of available defensemen. The study states that "Similarly, draft round had a relatively strong, significant effect on future defensive contribution." Farah & Baker (2021).

Sunk-cost Fallacy

Once again, we look at the work by Farah, L. & Baker, J. (2021). The authors simply set out to examine "sunk costs" in the NHL draft by conducting analytics on the relationship between draft order and playing time, with some controls in the analysis. Once the authors discovered many perks being handed out to first-round draftees (as opposed to later rounds), they were able to state that being a first-rounder meant a much higher upper-bound of talent development, given these perks.

There is also another piece of literature in sunk-cost fallacy in European football by Özaydın, S. (2022). The premise here is that, based on a "regression continuity design," can we extract any outcomes by relating "transfer fees and playing time?" Ultimately, the author finds that managers in England's Premier League may be coaching under an 'inefficiency' due to biased decisions, whereas managers in the top-flight league in Germany are not. So, this offers evidence of suboptimal player investment decisions based on managerial bias, which is relevant to potential offensive bias in the NHL draft. Such a phenomenon was briefly alluded to earlier in the study, but on a basic level, managers may prefer a certain player type or attribute. They may say that they have a knack for identifying such a thing, but this capability is overestimated and it is reflected in player choices.

Draft performance

NFL teams are trying very hard to mine talent out of the draft, but Duquette & Cebula, (2020) quoted another work that said some executives may be "displaying overconfidence" when it comes to assessing the 'top' draft selections, and that the draft as a labor market has yet to experience a correction to that bias. So, Duquette and Cebula proposed an "alternate metric," called 'weighted career approximate value." The authors "calculated the average weighted career AV" for drafts 1994—2003 and utilized a "best fit polynomial." Chiefly, the authors state that "Earlier NFL Draft Picks can be expected to yield more than later picks in performance-value terms." Duquette, C. M., & Cebula, R. J. (2020).

In the NBA, Maymin, P. Z. (2017), set out to program the NBA draft and see if a computer could outperform NBA executives and scouts. It is claimed that the program outdid human beings by "substantial margins." It continues by saying that NBA front offices have bastions of experience, but with that comes things like confirmation bias, personal "preferences" (see the section on Makar and the Flyers/NHL) and more. What the program can come in and do is perform nothing but analytics – it is a trained machine-learning model that isn't subject to thought processes like "is the Big Ten or the SEC better?" The piece states that "Historical NCAA college basketball performance is projected to subsequent NBA performance for prospects" and so Table 2 lists operational definitions of basketball statistics. In general, there is sufficient evidence across several leagues that managers do not make ideal draft decisions. Such outcomes will be examined here with emphasis on offensive vs. defensive bias.

Team Performance

The team performance section will consist of a wins model for NHL defensemen and predicting an NHL postseason. This is the final section of the literature review.

NHL defenseman wins model

The methodology presented by (Schuckers and Curro, 2013) for calculating how many 'wins' a player contributes to is a vital piece of literature. The study consisted of examining two different NHL seasons and the authors created a table that measured defensemen in "wins" based on the provided formula. The player would be worth "x more amount of wins per year" as compared to the average player or 'wins above replacement' (WAR), and this methodology is prevalent in other sports as well. In baseball, "WAR is both an imperfect stat and the perfect stat. Meant to encapsulate a player's total value to his team, it wraps offensive, defensive and baserunning contributions into one number" (Laurila, 2016). The results of this work show a table of defensemen from a given season, and it is an alternative way of visualizing a set or list of defensemen, and we note that is not exact to their original draft order. This is further evidence of potential draft bias and/or errors on an individual basis. One major distinction is that Schuckers and Curro wrote about analysis on an individual level, but this study is framed for the team level.

Predicting NHL playoffs

Nathan et al., (2017) took an innovative “wisdom of the crowd” approach to analyzing performance. The title says it all: predicting NHL playoffs with pagerank. In the end, the authors craft a model using several different parameters and they exclaim that “our ratings had a 70% accuracy for predicting the outcome of playoff series…” This work was included as it is directly relevant to the idea of investigating how certain variables affect playoff outcomes; in this study’s case, it is how defensemen are impacting winning percentages in regular season and playoffs.

Summary

The review process intentionally scoured quantitative works. The topics of these works tended to relate to the concept of Hockey Players, Sports Labor and Team Performance. These were chosen so that the reader’s understanding of specific analytics in ice hockey along with other sports could be enhanced. Most of the efforts that focused on ice hockey players aimed to try and isolate certain aspects of a player’s game; they all do not simply analyze a few stats, but they present a way of looking at a “direction” of the sport: offense, defense, transition, etc. Next, the section on ‘sports labor’ was designed to evaluate the practice of drafting in many different sports. These are all related in a roundabout way, but different sports were included for clarity. Lastly, the section on ‘Team Performance’ served the following purpose: laying down a prediction for what will happen in a sport’s most important season: the playoffs. This study moves forward by examining previously unstudied NHL drafting of defensive talent and the related team outcomes.

Chapter 3: Methods

Introduction

National Hockey League (NHL) clubs are constantly trying to craft championship rosters. Winning a championship is the ultimate goal of the sport. The ingredients in this recipe are extensive, but for this study's research question, the prospect of drafting high-consensus defensemen and its results will be explored. Two expansion drafts have occurred in the memory recent to this study being written, and teams are invariably trying to improve their draft philosophy and outlook in order to garner the maximum amount of value out of the draft. This chapter will cover the study's sampling, research design and its data analysis.

Sample

The data for this study include the existing results from each NHL draft from the period of 2007 to 2019 and subsequent results & outcomes. The significance of beginning with 2007 is this: the entire study will be within the NHL's salary cap era and each draft year examined had exactly 7 rounds. Even with the addition of the Las Vegas Golden Knights in the summer of 2017 resulting in the 2017 NHL draft holding 31 selections in round 1 instead of 30, there was still 7 rounds. Lastly, players eligible for the NHL draft come from all walks of life and all leagues, such as Denmark, Austria, Finland, Sweden, Canada and the USA. The NHL Central Scouting service does publish a ranking of players around draft time, and they are comprised of North American players and International players (NHL.com, 2023). However, in the sport of ice hockey, a team will often choose to stock up on organizational value by taking the "best player available" or draft for organizational necessity as opposed to simply following these rankings exclusively.

Data Collection

The data were collected from each year. Hockey-Reference was used to collect basic player stats. R is an open-source statistical computing program that was used in order to house large amounts of such data from the years 2007 through 2019. Natural Stat Trick (NST) is an online repository that tracks player-specific metrics like usage with teammates. By accessing the ‘player index’ section of the site, individual player data was retrieved. The study’s author performed the data collection. Data was managed in an Excel sheet and R file for statistical purposes. A single year’s results for winning-percentage were managed in an aptly titled Excel file, relying on syntax such as *2016Data*. Data sorting and cleaning was implemented to ensure maximum accuracy of data.

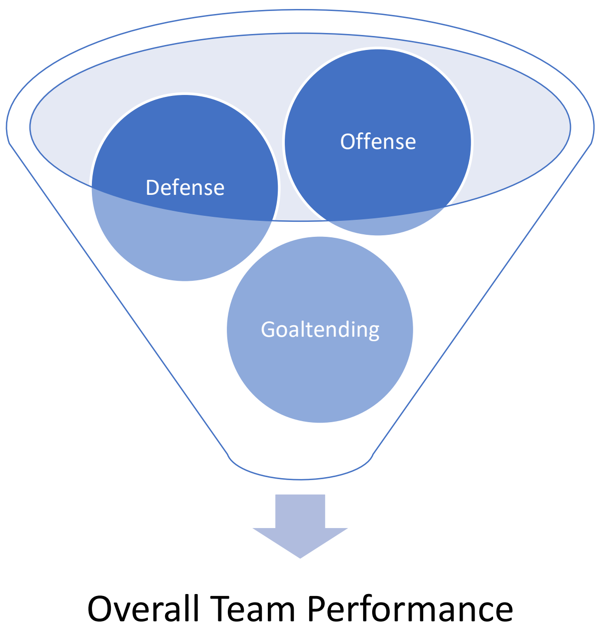
Data Management

Downloaded CSV files for each year’s draft results were read into an Excel sheet and saved in order to prepare for processing each year. Modeling that analyzed a relationship between elite offensive defensemen and regular-season success -- specifically, how offensive production affects winning percentage -- looks towards IBM SPSS to conduct plotting. Specific variable names and definitions for the quantitative analyses are outlined as follows.

Model/Variables

The ingredients of this study were chosen in order to fully encompass and measure the primary factors of team performance in the sport of ice hockey. The variables cover possible events and possibilities around a team's execution within a game. Figure 1 below illustrates this.

Figure 1: Factors contributing to overall hockey team performance



Variables

As the primary variables of interest, defensive contributions were split to account for the unique contributions from both draft acquisitions and the alternative contributions coming from players acquired in other ways, i.e. trades and/or free agent signings. The primary variables relevant to the central research questions were the number of players selected in the first or second round in the most recent two seasons (*DraftSelect)*, the utilization of those drafted defensive players (*DraftMin)*, and the utilization of non-drafted defensive players (*UndraftMin)*.

Offensive quality was included via the prior season's composite offensive ranking in the league using both Corsi statistics and goals scored per 60 minutes of game play (*TeamOffQuality)*, but also included possible new offensive play contribution from drafted defensemen (*OffensiveD)*. New offensive draftees were not included as a predictor however, as they would be viewed as a reference condition compared to the already included defensive draftee acquisitions. Finally, Goaltending was reflected in the overall performance of all of the goaltenders within a team by simply including saves versus all of the shots the team faced (*GoalieQuality)*.

As an additional control factor, the inclusion of era-specific divisions in the study accounted for conference realignment since the study spans so many seasons. Noll (2003) contrasts the two formats that a league in sport can adopt: round robin and tournament. Noll articulates that a tournament schedule – like the one used in the NHL – can create schedule imbalance based on division and conference. This is in opposition to the round robin format where every team plays each other a certain amount of times. (Noll, 2003). Next, the predictors in the study were chosen because they reflect not only paramount factors with respect to winning a game, but also the steps a franchise makes in order to acquire and use defensemen but also the players' variances.

Variable definitions and coding procedures are specified in Table 1.

Table 1

Variables	Definition
RSWinPct	Dependent variable for model 1. It will illustrate changes to the regular season winning% number. Possible values range from 0.0 to 1.0.
MakePlayoffs	Dependent variable for model 2. It depicts whether there was a playoff berth earned. Values = 0 or 1.

DraftSelection	Independent variable for all equations. This measures the following: A count of the 1^{st} and 2^{nd} round defenseman selections in the last three years. A draft-related hypothesis variable.
DraftMin_Z	Independent variable for all equations. Minutes played by drafted player who adheres to the following: Drafted in 1^{st} or 2^{nd} round in the last three years. 'Z is a Z-score or standard score of minutes value. A draft-related hypothesis variable.
UnDraftMin_Z	Independent variable for OLS equation. Z-score for minutes played by a player who: was not drafted by club A and signed with club A or who was never drafted in the first place. Continuous measure.
Offensive_D	Independent variable for all equations. It holds a draftee's Points/60 output. Continuous measure. Control Variable.
TeamOffQuality	Independent variable for all equations. This measures a team's offensive-quality as a rank. The rank was calculated by adding a team's Corsi-rank to their GoalsFor/60 Rank. The smaller the better (ie, 1+1 = 2, 2 would be the best). Continuous measure. Control Variable.
GoalieQuality	Independent variable for all equations. This measures the holistic save-percentage for a team by year. All saves divided by shots-against. Continuous measure.
Division	Independent variable for all equations. This denotes which division the team was in for which year.

Model

After all data was collected, the study adhered to the following analytical models for parameter estimates. First, an Ordinary Least Squares (OLS) regression was chosen because it allows an analysis of multiple variables impact on a dependent variable data that are both continuous and categorical. Then, a Logit regression was chosen because it allows an analysis on dependent variable data that is a simplification of many events and outcomes; in this case, coding 1 or 0 for playoffs made or missed.

Equation #1, OLS regression: $RSWinPct = B0 + \beta1DraftSelect + \beta2DraftMin\_Z + \beta3UndraftMin\_z + \beta4TeamOffQuality + \beta5GoalieQuality + \beta6Offensive\_D + \beta7Division + \varepsilon$

Equation #2, Logit Regression: $MakePlayoffs = B0 + \beta1DraftSelect + \beta2DraftMin\_Z + \beta3UndraftMin\_z + \beta4TeamOffQuality + \beta5GoalieQuality + \beta6Offensive\_D + +\beta7Division + \varepsilon$

Reference points such as $p<0.05$ and R^2 were provided in order to determine quality of statistical fit. Beta coefficients were tested against a mean 0 null hypothesis and statistically significant relationships were interpreted.

Chapter 4: Results

This study aimed to evaluate the value of defensemen in the game of professional ice hockey; namely, whether there is a relationship between regular-season winning percentage and drafted defensemen or undrafted ones during a 12-season period of the league's 'salary cap era'. Subsequently, it further measured whether the same cohort of defensemen affected playoff berths earned by clubs in the league. The analysis in this study was conducted in IBM SPSS Statistics to perform an Ordinary Least Squares (OLS) and Logit regression. The ordinary-least-squares regression examined the variables' effect on predicting regular-season winning percentage. Then, the Logit regression measured the variables' impact on a binary variable: 1 for playoffs made, 0 for playoffs missed. Before the specific regression results are discussed, some model assumptions must be presented.

First, the OLS assumptions. (Bastin, 2018)

- The regression model is linear in the coefficients and the error term
- The error term has a population mean of zero
- All independent variables are uncorrelated with the error term
- Observations of the error term are uncorrelated with each other

Then, the Logit assumptions. (Logistic regression – simple introduction, n.d.)

- Independent observations
- Correct model specification
- Errorless measurement of outcome variable and all predictors
- Linearity: each predictor is related linearly to ***e*^*B*** (the odds ratio)

All VIF statistics were below the cutoff of 5.0.

OLS Regression

Shown in Table 2, Descriptive Statistics were generated with the OLS regression. They can be summarized in this way: To reflect the study's 12 seasons beginning in 2007-08 to 2018-19, 30 NHL teams were included in the study's dataset. This yielded 360 data points. The table below lists each dependent and continuous variable's mean and standard deviation. Also in the OLS model, fit statistics and coefficients' significance levels are provided to illustrate the model's performance and how each individual independent variable predicted the dependent, respectively.

Then, in Table 3, the OLS output & summary are shown. Chiefly, *TeamOffQuality* and *GoalieQuality* are significant, $p<.001$. Notice that *DraftSelect* is significant – the Draft selections used by a team in the first and second round in the previous three years have a statistically significant effect on regular-season winning percentage. A final note is to comment on the division results from Table 3. Now-defunct divisions like *Central1* & *Pacific1* are statistically significant. The Coefficients reflect an imbalance for the period pre-realignment. The league re-shuffled the deck to smooth this imbalance.

Logit Regression

For the logit results, *TeamOffQuality* and *GoalieQuality* are still significant. None of the defensive draftee variables, *DraftSelect, DraftMinZ*, or *OffensiveD,* were statistically significant.

Table 2: Descriptive Statistics

	Mean	St. Dev	N
RSWinPct	0.4996	0.0893	360
DraftSelect	1.83	1.191	360
DraftMin	382.7567	1.0000	360
UnDraftMin	74.1429	1.0000	360
Draftee_p60	0.3772	0.6052	360
TeamOffQuality	31.27	14.39	360
Goalie_Quality	91.2	0.8703	360
Division	**%**		**N**
Pacific1	8.33	NA	30
Northeast	8.33	NA	30
Southeast	8.33	NA	30
Central1	8.33	NA	30
Atlantic1	8.33	NA	30
Atlantic2	13.33	NA	48
Central2	11.67	NA	42
Northwest	8.33	NA	30
Pacific2	11.67	NA	42
Metropolitan	13.33	NA	48

Table 3: OLS Output

Variables	B	Std. Error	t	Sig
Constant	-3.835	0.311	-12.316	<.001
DraftSelect	0.007	0.003	2.782	0.006
DraftMin_Z	-0.005	0.004	-1.168	0.244
UnDraft_z	-0.009	0.003	-3.036	0.003
Draftee_p60	0.008	0.007	1.177	0.24
TeamOffQuality	-0.004	0	-17.442	<.001
Goalie_Quality	0.048	0.003	14.24	<.001
Pacific1	0.032	0.013	2.49	0.013
Northeast	-0.017	0.013	-1.329	0.185
Southeast	-0.011	0.013	-0.838	0.403
Central1	0.035	0.013	2.716	0.007
Atlantic1	0.041	0.013	3.169	0.002
Central2	0.022	0.012	1.923	0.055
Northwest	0.024	0.013	1.862	0.063
Pacific2	0.018	0.012	1.515	0.131
Metropolitan	0.018	0.011	1.599	0.11

Model 1 Summary: Adj. $R^2 = 0.632$, $F(15, 344) = 42.04$; $p<.001$

Table 4: Logit results

Variable Name	B	S.E.	Wald	df	Sig	Exp(B)
DraftSelect	0.148	0.131	1.281	1	0.258	1.16
DraftMin_Z	0.046	0.231	0.04	1	0.842	1.047
UnDraft_z	-0.245	0.148	2.718	1	0.099	0.783
Draftee_p60	0.148	0.398	0.139	1	0.709	1.16
TeamOffQuality	-0.109	0.014	64.163	1	<.001	0.896
Goalie_Quality	1.846	0.244	57.471	1	<.001	6.337
Pacific1	0.458	0.617	0.553	1	0.457	1.582
Northeast	-0.215	0.652	0.109	1	0.742	0.807
Southeast	-1.324	0.653	4.108	1	0.043	0.266
Central1	0.877	0.711	1.523	1	0.217	2.403
Atlantic1	1.449	0.693	4.366	1	0.037	4.258
Atlantic2	-0.913	0.579	2.482	1	0.115	0.401
Central2	0.245	0.562	0.19	1	0.663	1.278
Northwest	0	0.636	0	1	1	1
Pacific2	-0.16	0.576	0.077	1	0.781	0.852
Constant	-165.181	22.061	56.061	1	<.001	0

Chi-Square (15,360) = 205.22, p<.001; Hosmer-Lemeshow: 0.476

Table 5: Classification Table

	Predicted v. Observed		
	MakePlayoffs	NO Playoffs	Correct (%)
MakePlayoffs	130	40	76.5
NO Playoffs	33	157	82.6
		Overall	79.7

In Table 3, the model came back as significant; p<.001. This indicates that the predictors were significant in forecasting Regular-Season winning percentage. Additionally, team-level offensive quality and goalie quality were found to be significant predictors with a level of p<.001. Table 3 shows that the adjusted R^2 value = .632, so this confirms that 63.2% of the variance in *RSWinPct* can be predicted by the variance of the independent variables in the model. To wrap this excerpt, the non-division related predictors that came out to be positively-significant were: *TeamOffQuality & Goalie_Quality*. Moving on, of the divisional predictors, it was found that the Northeast and Southeast were negative and non-significant. One thing to note: divisions noted with a “1” such as Central1 and Atlantic1 being shown as significant is noteworthy because it insinuates imbalance pre-realignment. Overall, from table 1, it must be stated that all divisions are relative to the not-included Atlantic2 division. An important figure to highlight includes *DraftSelect* as significant in Table 3. Using Draft Selections on defensemen in the first two rounds during a period of three years is a fruitful predictor of regular-season winning percentage.

For the logit regression, Table 4 presents the model fit and coefficients output. Table 5 provides a classification table with a matrix of playoff berths versus model predictions, 0=playoffs missed, 1=playoffs made. Overall, the model produced a 79.7% accuracy rate in predictions of playoff qualification. The model had a statistically significant fit with a <.001 significance level. The Hosmer-Lemeshow test returned a value of 0.476, and this is a fit statistic for logistic regression. A value less than .05 would indicate non-significance for the Hosmer-Lemeshow test.

Table 4 also shows odds ratio estimates for the predictors included in the model. The independent variables and a listing for each division are presented. In the NHL, teams are separated into divisions based on geography. From 2007-08 through 2012-13, they were the Atlantic, Northeast and Southeast in the Eastern Conference and the Central, Northwest & Pacific in the West. These divisions have re-branded into only the Atlantic, Metropolitan, Pacific and Central in the present, so terminology such as ‘Atlantic1’ and ‘Atlantic2’ were used to specifically identify divisions by era. Divisions were used to control for strength of schedule in the model. Next, in the ‘sig.’ column above, you can see that Goalie Quality and Team Offensive Quality were listed as statistically significant when adhering to an alpha α level of <.05.

Chapter 5: Discussion and Conclusion

Chapter 5 examines the original research questions and provides clarity to whether there is a relationship between drafted defensemen and team production and then if there is a relationship between offensively-minded defensemen and qualifying for the league playoffs. Then, the study's limitations, suggestions for future research and the conclusion will also be laid out.

Research Questions

Research Question #1 asked if there is a positive relationship between allocating draft capital to the defense position and team production as a result. To answer this, regular-season winning percentage and playoff berths as dependent variables were measured. We used the 'Z' or standard score of draftee minutes along with Undrafted Minutes as two of the independent variables. In Table 3, we found that Undrafted Minutes Z-score held a statistical significance of p=.003, while DraftMin_Z statistical significance was estimated as p=.244. When analyzing this impact, it can be deduced that for every 1 standard deviation increase in undrafted players use, you would see team winning percentage reduced by 0.9%. This exemplifies exactly how acutely a drafted defenseman is affecting a team's fortunes. A quick explanation for undrafted players is that on the free agent market, players are available for a monetary premium. Teams can either pay the player's market rate or they do not obtain his services. Due to the salary cap, paying these higher rates with varying lengths of contract years diminishes the amount of money available to fill out the rest of the roster. Finally, there is an argument for undrafted players holding a baseline level of quality that is useful, but not necessarily elite. Then, in crafting the analysis for this study, draftee minutes-played was liable to include rookies or draftees that made the team at any point in their development. Players are tasked with jumping from their pre-draft level to, at very least, non-professional hockey to professional, so the level of competition has gone up.

Research Question #2 inquired whether there is a relationship between the use of offensively-minded defensemen and qualifying for the league playoffs. Draftee_P60 is a measure of a draftee's Points/60, and it was not found to be statistically significant in any model. Offensive defensemen add a layer of assistance to a team's offensive conquests but would still be best-suited to be decent defensively and/or adhere to a coaching philosophy that limits such a player's playing time in the defensive zone. Draftee/P60 was not statistically significant in either analysis, and this can be interpreted by the following: it is not absolutely crucial to possess offensively-minded defensemen, at least in terms of the dependent variables.

Overall, both models produced coefficients that were statistically significant and the adjusted R^2 produced a rate of .632 in the OLS. This study could be used by firms to improve their efforts of winning a championship, but it also revealed many tangible variables in the sport of ice hockey of which were considered non-significant.

Limitations

Limitations of this study included time constraints. Originally, the author set out to perform the same analysis for the league's playoff rounds during the same years but had to stick with regular season. Another limitation was the exclusion of the Vegas Golden Knights, 2017—Present. They provided too few data points (with the study ending in 2018-19) to warrant making the study's dataset, so a repeated level of 30 teams was done for each year. You will see the Atlanta Thrashers only referred to as the Winnipeg Jets in this study as to maintain column integrity during data analysis and for clarity since they are the same franchise. The same goes for the Arizona Coyotes and Phoenix Coyotes. Then, it was briefly mentioned in the previous chapter, but there were no tangible data points included that reflect coaching philosophies or differing styles of play. The study's author understands that this has an effect of NHL outcomes, but the study only set out to measure quantitative data such as those included.

Recommendations for Future Research

As this study aimed to examine seasons during the league's salary-cap era and those pre-2020, a few recommendations could be made. First, a similar analysis could be performed for the league's postseason; one could examine the predictors' ability to forecast a championship. Increases to regular-season winning percentage and earning a playoff berth go hand-in-hand, so an increase to playoff winning percentage and winning a championship also correlate. Winning a title is the ultimate goal in the sport, so the insights created from doing that would surely be fascinating to see.

Conclusion

In conclusion, defensemen selected in the draft's first two rounds are responsible for a tangible effect on NHL team outcomes. However, it was found that offensively-minded defensemen do not present a statistically significant effect on playoff berths for NHL clubs, although there is an effect nonetheless. NHL clubs are awarded a standard amount of one first and one second round selection per year, and assuming these selections are not traded or surrendered, we can definitively say that spending some of them on defensemen has proven to be a lucrative business. So, in order to achieve the ultimate goal of winning a championship, it is perhaps more streamlined to simply focus on performing scouting and development at a high level instead of hyper-focusing on offensively-minded defensemen; this statement comes with its caveats because teams are after the best players available, and sometimes they are offensive-defensemen.

To re-iterate, the study's hypothesis statements were:

H1: Controlling for other team performance predictors, using 1st and 2nd round draft selections (draft capital) on defensive players will be positively associated with team performance.

H2: Controlling for other team performance predictors, recent 1st and 2nd round defensive draftee playing minutes will be positively associated with team performance.

H3: Controlling for other team performance predictors, using 1st and 2nd round draft selections on offensively oriented defensive players will be positively associated with team performance.

H0: Defensive player drafting, utilization and offensive orientation will have no relationship to team performance.

The hypotheses outlined on page 2 must be rejected or accepted. For *RSWinPct, we can* reject the null for H1, then fail to reject the null for H2 & H3. Further, for *MakePlayoffs*, we fail to reject all three null hypotheses. To visualize this, see Figure 2 below.

Figure 2

Hypothesis	RSWinPercent	MakePlayoffs
H1	Y	N
H2	N	N
H3	N	N

Figure 2 can be interpreted this way: With respect to regular-season winning percentage, only the use of 1st and 2nd round draft selections on defensemen (H1) was returned as positive. For making the playoffs, all hypotheses were accepted nulls. This means that for each analysis, the effect on H1, H2 & H3 were not statistically significant.

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