EVALUATING THE EFFICACY OF TALENT IDENTIFICATION AND DEVELOPMENT IN THE NATIONAL HOCKEY LEAGUE ENTRY DRAFT

LOJAIN FARAH

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Abstract

Objective: The overarching objective of this dissertation was to evaluate the efficacy of talent selection and development in the National Hockey League entry draft, as well as to inform talent selection and draft decisions to improve accuracy. This objective was carried out by addressing three main research questions: (a) How accurately can NHL decision makers predict future performance through the NHL draft (Chapter 2)? (b) How do the variables that predict draft status fare in predicting subsequent NHL success (Chapter 3)? (c) Do sunk cost effects exist in the NHL (Chapter 4)?

Methods: To address the first research question in Chapter 2, draft data (round and pick number) and subsequent NHL performance data were collected for the draft classes of 2007-2014. Two novel measures of offensive and defensive NHL performance were constructed using Exploratory Factor Analysis (EFA), then retrospectively compared such measures across all seven rounds of the draft using Kruskal-Wallis and Mann-Whitney U tests. In Chapter 3, pre-draft performance metrics, anthropometric measures, and subjective text-mined player attributes were collected. The relationship between such predictor variables and NHL order was studied using linear regression (part 1), before using Zero-Inflated Negative Binomial (ZINB) regression to study the relationship between the same independent variables and future NHL success (defined by games played). Lastly, Chapter 5 tested for sunk cost effects by using a hierarchical linear regression model which tested the relationship between draft order and NHL Time On Ice (TOI), while controlling for injury, trades, and on-ice performance.

Results: Findings from Chapter 2 showed NHL decision makers' ability to project future performance declines markedly after the first two rounds in forwards, and after the first round in defensemen. In Chapter 3, results indicated that forwards' penalty minutes, height, age, and lack of physical strength were overvalued in the draft, while plus/minus, board battles, backchecking ability, and hockey sense were undervalued. For defensemen, NHL teams overvalued CSB rankings, and undervalued playmaking ability, lack of physical strength, and work ethic/leadership. Last, findings in Chapter 4 found evidence of sunk cost effects, where players selected in the first round received significantly more playing time than their counterparts drafted later, even after controlling for confounding variables.

Conclusion: This dissertation uncovered substantial selection inaccuracies in the NHL entry draft, and identified a plethora of inefficiencies that drive these inaccuracies. Moreover, it highlighted that late draftees' development is compromised due to the sunk cost fallacy. As a result, this dissertation had significant implications for both research and practice. More specifically, it highlights avenues for future research to study draft related decision-making errors in more depth, and offers a range of suggestions to NHL personnel on improving their talent selection and development strategies.

Dedication

To mom, dad, and my brother - for their endless support and sacrifices.

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Table of Contents

List of Tables

List of Figures

Chapter One

General Introduction

Introduction

Success in the world of professional sports requires a continual search for talent. The pressure from ownership, fans and the media to win championships, or maintain a high level of competitiveness, drives sports organizations to identify and acquire talented athletes through various means. Such methods of talent identification and selection differ across sport systems and geographic regions. For instance, European soccer leagues employ a "free market" system, by which teams are allowed to sign young athletes, sometimes in early childhood, to long-term contracts. This allows teams to own the legal rights to such players throughout their developmental stages, and the ability to assign them to the first team once they have reached a certain age and level of experience. On the other hand, the four major North American professional sports leagues - namely, Major League Baseball (MLB), National Basketball Association (NBA), National Football Association (NFL), and the National Hockey League (NHL) - employ an entry-draft system, through which teams select young and promising athletes from a talent pool of players who are 18 years of age or older. In this particular system, every team is given one selection in each round of the draft to choose one athlete. In the MLB and the NFL, the draft order is inversely dictated by the previous year's standings; where the team that finished last selects first in the draft, the team that finished second-last selects second in the draft, and so on. On the other hand, the NBA and the NHL employ a lottery system, by which all teams that have missed the playoffs in the previous season enter a lottery to determine their position in the draft, while teams that have qualified for the playoffs are to draft in reverse order of playoff standings.

This entry-draft system serves two major purposes: first, it prevents the wealthiest teams from monopolizing talent by signing players to contracts that other teams could not match, and second, it attempts to ensure consistent parity and competitiveness in the league by granting poorly performing teams with higher draft picks, thus allowing them to select players who are deemed more promising, or of higher potential, in order to enhance team performance in the following years.

From a talent identification perspective, one might assume projecting future performance through an entry-draft is a rather accurate process, considering that selection is made in the late teens to early twenties, nearing the age at which players can perform at the professional level (i.e., draft selection represents a relatively short-term forecast). However, empirical evidence suggests otherwise, as the ability of professional teams to accurately identify talented draft eligible athletes and project their future performance has been heavily criticized in the literature. The following section outlines the findings of studies that have assessed the efficacy of athlete selection and development in the draft. Furthermore, it details the existing gaps in the literature that are addressed in this dissertation.

Literature Review

Draft accuracy in professional sports

As mentioned previously, the entry draft is structured in a way that grants poorly performing teams with opportunities to select athletes of higher caliber; this suggests selection number and player quality should, in theory, be negatively correlated. However, emerging evidence largely refutes this idea. For instance, in their analysis of NBA draft accuracy, Coates and Oguntimein (2010) found that selection number does not predict offensive production nor rebounds in the NBA, even after controlling for collegiate performance. The researchers also added that 60-70% of NBA performance metrics are unexplained by neither collegiate performance nor draft order; suggesting that player selection is a "risky and uncertain endeavor" (p. 22).

The dynamic and unpredictable nature of talent development is indeed a major factor in making the draft such an uncertain endeavour; nonetheless, decision makers (i.e., scouts, general managers or presidents) also bear part of the responsibility for their heuristic-prone selection methods. To elaborate, NBA decision makers have been shown to overvalue total scoring when drafting an athlete without paying enough attention to shooting efficiency. As a result, it is not necessarily the *best shooters* that get selected first, but the ones that simply *shoot more* (Berri et al., 2011). Another overvalued factor is a player's appearance in the Final Four of the National Collegiate Athletic Association (NCAA) March Madness tournament (MM), as advancing to this stage of the tournament enhances a player's draft ranking by 12 slots. That is not to suggest that success in MM is irrelevant to NBA success; in fact, much of the individual success a player experiences in MM translates into being an all-star in the NBA (Ichniowski & Preston, 2017). However, it is the reliance on appearance in the Final Four while overlooking the nuances of performance throughout the tournament that results in inaccurate talent selection. By the same token, some important performance attributes are often overlooked on draft day. These include defensive measures such as rebounds and steals in college, which have been shown to predict NBA success fairly well yet are largely overlooked by decision makers (Berri et al., 2011).

Findings from NFL-focused research have mostly aligned with that of the NBA, with some notable exceptions. For instance, Boulier et al. (2010) found a significant negative relationship between draft order and performance/career length of NFL players. Furthermore, over 90% of wide receivers selected in the first round played ≥ 4 seasons and over 50% played ≥ 8 seasons, compared to 70% and 40%, respectively, for players selected in the second round.

Similarly for quarterbacks, those selected first overall have a quarterback rating[1] of 15 points more than their counterparts selected 31st (the first pick of the second round). Despite such results, the authors still emphasized that talent selection is by no means a perfect process in the NFL. In fact, 40% of the quarterbacks selected in later rounds between 1974 and 2005 outperformed their counterparts chosen in the first two rounds of the draft. Similarly, a 42% error rate was observed for wide receivers drafted in the same period of time.

While Boulier et al.'s study was thorough, the use of quarterback rating to assess NFL performance - and in turn the accuracy of talent selection in the draft - is flawed in several ways. First, the four components of this rating are weighted arbitrarily and not in accordance to the quarterback's contribution to team wins. Second, it disregards running with the ball and only accounts for passing, which creates an incomplete measure of performance. Finally, this measure was created in 1971, long before the extensive advanced analytics used today were tracked and computed. This may explain the contradictory findings of Berri and Simmons (2011), who used QB score[2] to evaluate performance in the NFL. Their results showed that quarterbacks drafted 11th-90th outperformed those drafted in the top 10 on a *per-play basis*. This suggests players taken in the top 10 simply receive more playing time but are not actually of better quality, a concept that will be discussed in more detail in the second section of the literature review. These mistakes in forecasting future performance are again mainly due to decision makers placing more value on variables such as height, 40-yard dash time, Wonderlic score and coming from a recognizable college division than they place on actual on-field performance.

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[1] Quarterback rating is a metric used to assess the performance of quarterbacks based on pass completion rate, pass yards, interceptions and touchdowns.
[2] QB score is a relatively newer performance metric that accounts for 8 different attributes of quarterbacks.

This overreliance on anthropometric measures to evaluate talent in football is not exclusive to the position of quarterback; physical tests conducted in the draft combine have been shown to accurately predict draft ranking of running backs, wide receivers, offensive linemen, defensive linemen, defensive backs and linebackers (McGee & Burkett, 2003), despite evidence showing no relationship between draft combine scores and subsequent performance in the NFL, with the exception of sprint tests in running backs (Kuzmits & Adams, 2008). Combine scores can be deceiving during talent identification for two main reasons: first, such physical tests measure only one specific quality of an athlete (e.g., their ability to jump high) while partially or fully isolated from the field of play. As a result, scores are not indicative of how the athlete utilizes these capacities in game settings (e.g., while carrying out other tasks such as coordinating with teammates and shutting down the opposition). Second, as athletes and their agents became aware of the importance of combine testing on draft status, they began to enroll in physical and psychological programs designed to prepare them for the combine and enhance their scores, which erroneously escalates the value of the combine.

Draft accuracy in the NHL

Unlike the other professional sports leagues, there is a relative scarcity of research focusing on the efficacy of scouting and talent selection in the NHL entry-draft. In fact, a recent systematic review found that out of 17 peer-reviewed studies examining draft accuracy in North American leagues, only one evaluated the NHL draft, compared to three, seven, and six focusing on MLB, NBA, and NFL drafts, respectively (Johnston, Farah, Ghuman, et al., 2021). For the most part, research on the NHL draft has focused on the apparent discrimination and prejudice displayed against French Canadian and European players in the past (Marple, 1975). Data from the 1980s and early 1990s had shown that French Canadian players end up producing superior offensive performance metrics than their English Canadian counterparts by an average of 5-10 points, which translates into a 10-20% differential in performance (Lavoie et al., 1987). Despite their offensive production, French Canadian players seemed to face more entry barriers than English Canadian and American players due to geopolitical differences within Canada, and the common notion among NHL scouts at the time that players from those regions were defensively irresponsible and lackadaisical (Lavoie et al., 1987). Using data from the 1993-1994 season, Lavoie (2003) tested the validity of this notion by comparing the defensive play of French Canadian and European players to that of English Canadian and Americans. Results showed that that the two groups had very similar defensive capabilities, yet French Canadians and Europeans were overlooked and discriminated against in the draft.

Although discrimination against French Canadian and European players was a well-known issue in the NHL, the relevance of Lavoie's findings in contemporary settings is questionable for several reasons, not the least of which is the limited nature of his measures of defensive capabilities. For example, one set of measures was simply height and weight, which were not validated to confirm they were relevant proxies for defensive play. In fact, one could argue that heavier players are more prone to being out-skated by lighter players, putting them at a defensive disadvantage. Similarly, he also measured plus/minus, a performance metric that simply subtracts goals against from goals for while a player was on the ice, which does not account for players' usage, quality of teammates nor quality of opposition. This metric has since been replaced by more elaborate advanced analytics that account for such variables and more. He also focused on penalty minutes based on the rationale that penalty minutes measures the "intimidation factor" of a player and therefore his defensive prowess. There are three reasons why this measure is not applicable; first, taking a penalty results in one's team being shorthanded, which, in reality, puts them at a substantial defensive *disadvantage*. Second, fighting results in a 5 minute penalty where the player is ineligible to play which means he cannot contribute defensively or offensively. Third, fighters have become largely obsolete in today's NHL, meaning that even if penalty minutes is indeed a good measure of defense, it does not capture a contemporary style of defense play. Finally, he considered 'being a part of the penalty kill unit' (i.e., being utilized when one's team is shorthanded) as a key measure of defensive skill; however, while this may be a reasonable proxy for defensive play, many good offensive players are utilized on the penalty kill while many defensemen are not (Lavoie, 2003).

Importantly, these criticisms are not meant to invalidate the work of Lavoie or others. In fact, such research utilized the best metrics available at the time, when even simple and basic metrics – by today's standards – such as blocked shots or hits were not tracked. The more relevant issue at hand is that prior research on the NHL draft can be updated with more advanced measures in order to accurately capture the state of talent selection in today's league. For instance, the last study to assess NHL franchise success in talent selection relied on data from 1969-1995 (Dawson & Magee, 2001). Over the past 25 years, the league has undergone substantial structural changes that warrant an updated ranking. First, the NHL has added five franchises (Columbus Blue Jackets, Minnesota Wild, Nashville Predators, Vegas Golden Knights, and Seattle Kraken) after the publication of the previous ranking. Second, the length of the draft was reduced from 9 rounds to 7 in 2005, which decreased the size of the available talent pool. Third, the introduction of the "draft lottery" in 2005 introduced the element of luck into talent selection, which means that teams are forced to invest more resources into talent identification as they are no longer guaranteed to draft promising prospects by simply having a losing record the previous season.

It is important to note that with the recent rise of advanced hockey analytics, more NHL-focused analyses have been conducted. However, such work has either been published in media outlets (e.g., sports networks and blogs) or in independent hockey conferences (Chang, 2011; Davis, 1991; Schuckers, 2016; Stimson & Cane, 2017). As a result, findings have not been empirically replicated through peer-reviewed academic research. Moreover, the majority of this work has focused on player usage and salary distribution, leaving draft-focused analyses in the NHL quite scarce.

To my knowledge, only two analyses have focused on the efficacy of talent selection. The first, by Schuckers (2016), showed that using a simple model of players' (a) basic physical parameters (height and weight), (b) performance metrics (points per game and goals against average), and (c) pre-draft ranking from the NHL's Central Scouting Service (CSS) improved the accuracy of talent selection substantially. The original draft order (i.e., the order in which players were actually drafted by NHL general managers) only correlated with "NHL success" by 0.4, while Schuckers' model had a Spearman's correlation coefficient of 0.6. Although this finding puts the forecasting ability of NHL decision makers into question, the outcome variables used by Schuckers to measure NHL success consisted of NHL games played and Time On Ice (TOI). While these two measurements provide a general idea of success, they do not account for contextual differences between playing positions. For example, starting goaltenders in the NHL typically rest for 20-30 games a season, while – barring injury - defensemen and forwards play all 82 games, meaning goaltenders accumulate far fewer games over their careers. In addition, each hockey team is comprised of 12 forwards and 6 defensemen, therefore, total TOI is distributed differently between each position, which results in first pairing defensemen accumulating substantially more minutes than forwards.

The second analysis was by Seppa et al. (2017) and used text-mining techniques of scouting reports to extract useful information and enhance talent selection. However, Seppa et al.'s measure of successful talent selection consisted of success in the American Hockey League (AHL), a minor professional league a tier below the NHL. While the AHL is indeed one of the highest levels of professional hockey, the ultimate goal of the entry draft is to select future NHL talent. In addition, success in the AHL does not necessarily translate into the NHL given the substantial discrepancy in the level of competition between the two leagues. For instance, Keith Aucoin is considered one of the best AHL players of his generation, accumulating 857 points in 769 AHL games, while only producing 49 points in 145 NHL games. Collectively, this suggests a lack of empirical and contemporary research focusing on the efficacy of talent selection in the NHL.

Furthermore, talent selection is followed by a lengthy process of *talent development*. This process, although not characterized by a unified definition, essentially describes a period during which drafted athletes are given opportunities to gain experience by playing at a higher level, while maturing from a technical, physical and psychological standpoint. For instance, after being drafted, a player would either compete in Europe, college/junior leagues, or be assigned to the AHL affiliate or the NHL club itself. During this period, the player's ice time is monitored closely by the team to ensure he is accumulating sufficient experience in different on-ice situations (i.e., 5v5, penalty kill, power play, etc.). In addition to playing time, a player is often given individualized coaching sessions (on-ice or video based) to strengthen certain weaknesses in his game. Likewise, personalized strength training regiments along with mentorship opportunities are provided to help the prospect mature physically and personally. Therefore, in order for talent selection to be optimized, precise methods of subsequent development are needed. Similar to talent selection, however, talent development remains understudied in the NHL. In particular, one of the areas pertaining to development that has been explored in other sports drafts but not in the NHL is the 'sunk cost effect'.

The sunk cost effect

Although the main purpose of the draft is to provide an avenue for talent identification and selection, the salary/bonus structure that is integrated within the draft system has long lasting implications for player development. To elaborate, athletes receive varying salaries and bonuses depending on the position in which they were drafted - the earlier the draft pick, the higher the monetary reward. In the NFL, for example, a player selected with the last pick of the first round would receive a $10 million contract with $5.3 million in bonuses, whereas the player taken first overall would receive a $35 million contract with $23.5 million in bonuses. Similarly in later rounds, the value of contracts range from $4.5 – $7.6 million in the second round, $3.3 – $4.2 million in the third round, and $2.5 – $3.3 million in rounds 4 through 7 (Smith, n.d.). Such large disparities in monetary rewards between draft rounds has created what economists refer to as a 'sunk cost effect'. Within the fields of economics and behavioral psychology, this term describes the human tendency to continuously and wastefully invest time, money and effort towards a fruitless endeavour, despite the fact that the costs far outweigh the rewards, simply because one has already committed to said endeavour (Staw, 1976). Or, in the words of Garland (1990): "throwing good money after bad". Within the context of sport, the sunk cost effect refers to teams irrationally providing their highly drafted athletes with more playing and training opportunities than their counterparts drafted in later rounds, *regardless of performance outcomes*, in an attempt to justify the large irreversible monetary investments that have been made. In addition to financial commitment, merely selecting an athlete in the draft is an irreversible decision, and each selection represents a potentially missed opportunity to select another athlete that could develop into a better player. Therefore, draft selection also represents a psychological sunk costs that could lead to irrational decision making in the future.

Staw and Hoang (1995) were the first to exhibit evidence of the sunk cost effect in professional sports through their examination of the 1980-1986 NBA drafts. Their results indicated that players taken early in the draft played more minutes, had longer careers and were less likely to be traded than their counterparts selected in later rounds, even after controlling for their actual on-court performance. Furthermore, they showed that an increase in selection number by one pick resulted in a 23 minute decrease in total playing time, a 3 percent increase in career mortality risk and a 3 percent increase in the likelihood of being traded. This leads to first round draftees playing 552 more minutes in their second year, averaging 3.3 years longer in the NBA and benefiting from a 72% lower risk of being traded than their second-round counterparts. Of course, one could argue first round picks are more promising and therefore should receive more playing time in order to develop and live up to their potential. For that reason, Staw and Hoang conducted additional analyses, which showed that while increased playing time does indeed improve subsequent performance in the following season, the interactions between draft order and playing time did not significantly predict subsequent performance. This suggests allocating playing time disproportionally between first and second round draftees is not a sound decision. Evidence of the sunk cost effect in the NBA were replicated by Camerer and Weber (1999), who conducted the same analyses for the 1986-1991 drafts. Results from this study revealed irrational allocation of playing time due to draft-induced sunk costs. However, this effect was lower in magnitude and for a shorter duration than in Staw and Hoang’s study, as it seemed to strongly exist in years 2 and 3 after the draft, but diminished in years 4 and 5.

Contrary to the findings of these two studies, analyses of more recent (i.e., 1995-2005) NBA drafts showed little to no sunk cost effects (Leeds et al., 2015). Such discrepancies in findings may be due to Leeds et al. using Wins Produced per minute (WP48) as their main performance metric, which is a relatively new concept that was not available when Staw and Hoang's (1995) or Camerer and Weber's (1999) studies were written, and may potentially capture performance more accurately. Another possible reason is the use of local linear regression discontinuity analysis in Leeds' study, as opposed to global linear models in the two previous papers. However, the more probable explanation of these conflicting results could stem from the NBA standardizing its rookie contracts in 1995, meaning that drafted players receive contracts that are set by the league based on their draft order and are not freely negotiated between teams and players' agents as was the case in the previous two studies. Not only have rookie contracts' value decreased by 30-50% after this change, but the length and value of such contracts are now exogenously decided, which removes some of the responsibility and commitment from teams' general managers. Consequently, this could have decreased the magnitude of the sunk cost effect. This is in agreement with earlier research showing a sunk cost effect only existed when decision makers were the ones directly responsible for promoting their employees and incurring the costs (Bazerman et al., 1982).

Since Staw and Hoang's seminal paper, research has continued to explore this effect in other leagues. For example, a study on NFL talent development indicated players selected near the cut off between the first and the second rounds started significantly more games than those drafted in the second round, despite not being any more productive in terms of performance. In fact, a 10% increase in salary cap value resulted in 2.7 more games started (Keefer, 2017). Considering that the NFL season consists of only 16 games, sunk costs seem to have a substantial effect on games played regardless of performance. Not only has this effect been observed following the NFL draft, but after free agency as well. Keefer (2015) has shown that players who sign big contracts in free agency receive significantly more playing time simply as a virtue of their earnings rather than performance.

While literature in the fields of athlete development and sport economics have uncovered a great deal about the sunk cost effect in professional sports, the NHL remains an untapped area of research with many unanswered questions. For starters, NHL draftees' salaries and bonuses do not vary based on draft order; as all players who are signed to an Entry Level Contract are compensated equally at $925,000 annually. Furthermore, the NHL has a deep farm system composed of two lower-tier leagues known as the AHL and the East Coast Hockey League (ECHL). This provides draftees with an opportunity to develop and become accustomed to professional hockey; therefore, sunk cost effects may be nullified by the time these players are ready to transition into the NHL (Koz et al., 2012). Although these are plausible hypotheses, one cannot rule out the existence of sunk cost effects in the NHL for three reasons. First, such hypotheses, while logical, are yet to be empirically tested and supported. Second, although all rookies are compensated equally, this does not eliminate the possibility of a sunk cost effect since - as mentioned previously – a selection made in the draft is an opportunity foregone to draft another athlete an in and of itself represents an irreversible commitment and a sunk cost (i.e., a psychological sunk cost rather than a financial one). Finally, even though the NHL has a deep farm system, it is not clear whether first round draft picks are favored within those developmental leagues in terms of playing time and opportunities for NHL call-ups. Examining these effects in the NHL would add to our knowledge on talent development in this league, and therefore our overall understanding of this effect in relation to varying types of contractual obligations across sports leagues.

Objectives

The overarching objective of this dissertation is to evaluate the efficacy of talent selection and development in the National Hockey League, as well as to inform talent selection and draft decisions to improve accuracy. This will be carried out by examining and answering the following three research questions: (a) do NHL performance metrics differ within and between draft rounds? (b) How do the variables that predict draft status fare in predicting subsequent NHL success? (c) Does the sunk cost effects exist in the NHL? Each of these research questions will be addressed separately across the following chapters of the dissertation.

Significance to the field

The proposed dissertation will make several contributions to the field of talent identification and development. First, it will provide a novel and thorough assessment of the current state of athlete selection in the NHL, a league that has been largely understudied relative to the overall volume of talent identification research. Second, it will inform NHL decision makers of the predictors of future success, which would in turn improve the accuracy of talent selection. Third, this project will shed light on the efficacy of development past the point of selection by testing for sunk cost effects. To the best of my knowledge, no peer-reviewed empirical research has used such a wide variety of variables (e.g., games played, position-specific performance metrics, advanced analytics, etc.) to assess NHL talent selection accuracy. Similarly, no studies have explored the existence, or magnitude, of the sunk cost effect in this league. By addressing these gaps in the literature, this project will enhance our understanding of talent identification and development in hockey and test the generalizability of findings from other professional sports to the unique context of the NHL.

Chapter Two

Accuracy from the slot: Evaluating draft selections in the National Hockey League

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**This manuscript has been presented in the formatting that has been accepted and published in the respective journal. References are included at the end of the dissertation starting on page 114.*

Abstract

The National Hockey League (NHL) entry draft is a process wherein teams make sequential selections from a pool of eligible players. Given the young age of prospects, drafting requires long-term forecasting of future performance under a high level of uncertainty. This study assessed the selection accuracy across all seven rounds of the draft, as well as between lottery and non-lottery picks within the first round. NHL performance data was collected for all forwards (N = 956) and defensemen (N = 558) drafted from 2007-2014. In both groups, Kruskal-Wallis *H* tests conducted between draft rounds revealed a significant, relatively strong, overall effect of draft order on future performance. However, Mann-Whitney U post-hoc tests showed projecting future performance of forwards was only accurate in the first two rounds, while for defensemen, selection was only accurate in the first round. Moreover, forwards selected with lottery picks in the first round outperformed their non-lottery peers offensively but not defensively. As for defensemen, those selected with lottery picks did not differ from their non-lottery peers in offensive or defensive performance. Our findings highlight substantial inaccuracies in the NHL draft, particularly past the first two rounds of selection. We offer multiple possible explanations driving such inaccuracies that could form the basis for further work in this area.

Keywords: National Hockey League, talent identification, draft accuracy, decision making

Introduction

The success of a National Hockey League (NHL) organization relies on a wide variety of systemic and organizational components, from the coaching staff and board of directors, to the strength and conditioning and sport psychology personnel. Arguably, however, the most essential element of sustainable long-term success lies in the amateur scouting department, whose purpose is to supply the organization with a continuous stream of young, high-caliber players. In the words of former NHL general manager, Brian Burke, "the lifeblood of the National Hockey League is scouting" (Malloy, 2011, p. IX).

The primary method for scouting departments to identify and select youth talent takes place through an annual event known as the "entry draft". During this process, all 31 NHL teams take turns selecting (drafting) from a pool of promising 18 year old ice-hockey (hereafter simply 'hockey') players who compete in collegiate, junior, or European leagues.[3] This selection process occurs over seven rounds, wherein every team is given one selection (i.e., one draft pick) per round. The order in which teams make their selections is somewhat unique. For instance, picks #1-15 of the first round are decided by a lottery involving all 15 teams that did not qualify for the playoffs the year prior, and are referred to as "lottery picks". Subsequently, teams that qualified for the playoffs receive picks #16-31 – also known as "non-lottery picks" – in reverse order of their playoff performance (i.e., the last pick is given to the team that won the Stanley Cup in the previous year). This same order of selection is then repeated in the following six rounds (see Appendix A for more information). Through their selection, the team earns the exclusive rights to negotiate with and sign the player to a professional contract. The goal of the draft is to prevent

[3] Age requirements differ based on nationality; North American players must be 18-20 years old and European players must be 18-21 in order to be considered eligible for selection

talent monopolization by wealthy teams, who may otherwise offer contracts to players that other teams could not match. Granting draft picks in reverse order of team performance is based on the assumption that athletes drafted early are of higher quality and potential, and will therefore provide poorly performing teams with the help they need to strengthen their rosters. This suggests draft pick number and future success of draftees should, *in theory*, form an inverse linear relationship. However, literature on NHL draft accuracy suggests the reality of selection is otherwise.

Upon reviewing every draft decision made between 1981-2003, Tingling (2017) reported that almost 60% of draftees did not end up playing a single NHL game. Of the 40% who did, only half played 160 games or more. To put this number in perspective, the NHL season is 82 games long, meaning that only 20% of all draftees go on to play two or more NHL seasons throughout their careers. Such results suggest the vast majority of draft choices are not “successful” by this particular standard. While Tingling’s findings are partly due to the limited number of vacant NHL roster spots compared to the sheer number of yearly draftees, they may also be driven by inaccuracies in talent identification in the draft. For instance, Koz et al. (2012) showed that players drafted in the first and second rounds have longer NHL careers, on average, than their counterparts selected in later rounds. However, from the third round onwards, selection accuracy diminished, as no differences in Games Played (GP) were observed between rounds three, four and six. Interestingly, players taken in round 6 had longer careers than those taken before them in round five.

The convergence of career length across later rounds suggests scouts’ ability to identify future NHL players decreases after the second round, as the available pool of athletes dwindles in size and become more homogenous in perceived quality. Players selected first overall (i.e., the first pick of the first round) have a 98% chance of playing 200 NHL games or more. This probability then declines in a steep linear fashion until the middle of the 2nd round, after which it begins to decrease in a much slower and inconsistent trend (Schuckers, 2011). Similar results were observed by Shoniker (2015) via survival analysis, which showed that first and second round draftees were superior to the rest of the draft class in terms of NHL GP. However, the players' likelihood to survive the benchmark of 700 games begins to converge past the third round and the probability of players drafted in rounds five, six and seven to survive any "X" number of games in the NHL is virtually identical. Likewise, players' Goals Versus Threshold (GVT) – a metric representing goals created relative to replacement value –tends to decline heavily past the first round, and stabilizes in the later rounds of selection (Schuckers & Argeris, 2015).

Although past research has uncovered a great deal of information on selection accuracy, some gaps remain. For instance, NHL GP is used in almost all cases as the standard measure of success because it represents the length of a player's career. However, there are two main limitations to this approach: First, GP merely indicates that a player has performed at a minimum required threshold to sustain an NHL roster spot for a certain time period, and does not provide any measure of his actual on-ice contributions to the team, nor his offensive and defensive output (Nandakumar & Jensen, 2019). This point was perfectly illustrated by Schuckers (2011) who cited Zigmund Palffy and Kent Manderville as two players with comparable GP (684 and 646, respectively), yet the former scored 713 points over his career, while the latter scored only 104 points. Indeed, this is not to suggest that point scoring is the sole measure of player success in the NHL; rather, to highlight that there is more to a player's career than the number of games accumulated. Second, draft data from the National Basketball Association (NBA) and National

Football League (NFL) suggests first round draftees often receive preferential treatment from their teams, as they are afforded more playing opportunities than their performance would justify, mainly due to heightened expectations surrounding such players, and due to sunk cost effects associated with their high draft status.[4] While it is not yet clear whether such sunk cost effects exist in the NHL, it is certainly possible due to similar draft structures within these leagues. This may in turn inflate the number of games accumulated by first round draftees and skew the analysis of draft accuracy. Although Schuckers and Argeris (2015) accounted for this limitation of GP by using GVT, the field of hockey analytics has expanded considerably in the last decade since the creation of GVT in 2009. There is now a plethora of metrics that can capture different facets of NHL performance, such as puck possession, quantity and quality of scoring chances, quality of teammates, and so on.

Another notable gap is the tendency to focus on inter-round comparisons by aggregating the performance of players in each round, which could mask potential intra-round variability that exists in the data. This is particularly true for first round draftees, whom have repeatedly been shown to be superior – on aggregate – to draftees from later rounds; yet, it is unlikely that all first round draftees enjoy the same level of NHL success. In fact, lottery draftees (i.e., those selected with lottery draft picks #1-15) appear to be held in much higher regard by scouts and decision makers than non-lottery ones (those selected with picks #16-31), despite being in the same round. Exploring this variation could expand our knowledge on talent selection within this particularly elite subgroup of the draft.

[4] The sunk cost effect manifests in professional sports when teams escalate their commitment towards early draftees by giving them more playing time, despite evidence of poor performance, in an attempt to justify selecting them in the draft (Camerer & Weber, 1999; Keefer, 2017; Staw & Hoang, 1995).

By addressing the aforementioned gaps in the literature, we may be able to specify where talent identification in the draft is strong or weak, thereby offering a guide to both researchers and practitioners to study and address such weaknesses accordingly. As such, the aim of this paper is two-fold: (a) to assess selection accuracy between all rounds of the NHL draft by using advanced analytics that capture multiple facets of players' post-draft performance, and (b) to assess selection accuracy *within* the first round, by comparing the subsequent NHL performance of lottery and non-lottery draftees. We define selection accuracy according to whether players drafted in a certain round subsequently outperform those selected in the successive round, and whether lottery draftees outperform their non-lottery peers in the future. To address both purposes, we tracked players' performance within the first five seasons after their draft date. This number of years was chosen as almost all NHL players begin their careers within that time span (Shoniker, 2015). Moreover, restricting the evaluation period to five years allows for the use of recent draft classes, making the data more contemporary and relevant to current settings.

Methods

Sample

NHL draft data were collected from hockeydb.com[5] for all forwards and defensemen selected into the NHL from 2007-2014 (N = 1514), including the round in which a player was drafted and the specific pick number. This particular time period was chosen since most advanced performance metrics were only tracked in the NHL from 2007 onwards (Nandakumar & Jensen, 2019). This includes most measures of puck possession and quality of scoring chances (e.g., Corsi, Fenwick, expected goals, etc.), many of which were utilized in our analysis.

[5] Hockeydb is a vast online database that contains draft information and basic performance metrics for professional and amateur hockey players. It is widely considered as the most reliable source of data for NHL focused research (Deaner et al., 2013; Schuckers, 2016; Shoniker, 2015).

Similarly, because this study relied on performance data within the first five years post draft, 2014 was considered the cut off year for the sample to allow collection of data up to the end of the 2018-2019 season.

Variables

A combination of offensive and defensive performance metrics were collected for the first five NHL regular seasons post draft from corsicahockey.com. This site relies on official play-by-play data retrieved from the NHL itself, and aggregates such data into metrics that the NHL does not offer on its site (Naples et al., 2018). Accordingly, data utilized by this site is reliable, making it one of the most widely used sources of advanced analytics in hockey research (Knodell, 2019; Nandakumar & Jensen, 2019; Naples et al., 2018). All metrics were 5-on-5 (i.e., excluding power play and penalty kill) to control for coaches' deployment of players on special teams. To control for quality of teammates, which may confound a player's performance, metrics were measured on a relative-to-teammates basis (denoted by "Rel"), wherein the quantity/quality of scoring chances and goals – both for and against the team – were measured when the player was on the ice compared to when he was off the ice. In addition, all metrics were standardized per 60 minutes to control for the amount of playing time a player receives, which is partly driven by coaches' decisions, and to adjust for the 2012-2013 lockout shortened season.

In addition to the abovementioned selection criteria for variables, it was important to collect both offensive and defensive metrics, as focusing on one over the other would skew the analysis in favor of players who only play a certain style (i.e., either defensive or offensive minded players). Given that the ultimate goal for a hockey team is to outscore the opposition in order to win, we collected metrics that reflect players' ability to (a) help their team maintain possession of the puck, as that would make one's team more likely to score and less likely to be scored on, (b) generate scoring chances and goals for their team, and (c) deny scoring chances and goals against their own team. As such, the following seven variables were collected: *P/60* - points scored (goals plus assists) per 60 minutes of ice time; *RelFF/60* - quantity of unblocked shot attempts for the team when the player is on the ice compared to when he is off the ice; *RelxGF/60* - quality of scoring chances for the team when the player is on the ice compared to when he is off the ice; *RelGF/60* - number of goals for the team when the player is on the ice compared to when he is off the ice; *RelFA/60* - quantity of unblocked shot attempts against the team when the player is on the ice compared to when he is off the ice; *RelxGA/60* - quality of scoring chances against the team when the player is on the ice compared to when he is off the ice; *RelGA/60* - number of goals against the team when the player is on the ice compared to when he is off the ice.

Pre-analysis

Due to potential multicollinearity between performance metrics, and to avoid inflating Type I error by comparing each metric across draft rounds, it was necessary to reduce the number of metrics into to a smaller set of variables. To do so, both Factor Analysis (FA) and Principal Component Analysis (PCA) were considered. However, there are key fundamental differences between the two that were taken into consideration. First, FA uncovers the *underlying latent constructs* of hockey performance and estimates factors that have conceptual meaning. Such factors, given their meaning and interpretability, can be used as indicators of the contribution of the player to his team, and in turn used as indicators as to whether drafting him was an accurate decision. On the other hand, PCA merely decomposes variables into weighted linear combinations that are not similarly interpretable and do not inherently have conceptual meaning (Field, 2009; Tabachnick & Fidell, 2007). Second, PCA operates under the assumption that no measurement errors exist in the data (Osborne, 2014), which cannot be guaranteed in a fast-paced sport such as hockey where human error in play-by-play data is possible. Therefore, FA was chosen over PCA for this study design.

Furthermore, the FA conducted in this study was exploratory rather than confirmatory, since (a) to our knowledge, no prior research has indicated specific underlying factors of NHL performance which we would wish to confirm, and (b) although metrics were collected to capture offensive and defensive aspects of players' performance, we did not operate under certain hypotheses regarding the specific intercorrelation between these metrics, nor did we hypothesize the nature of the latent constructs as there could be many (e.g., defensive performance, puck possession maintenance, scoring ability, shot suppression ability, etc.). Subsequently, an Exploratory Factor Analysis (EFA) was used to enable the data itself to uncover measures of hockey performance.

However, because of differences in playing style and positional needs, this factor analysis was conducted separately for forwards and defensemen as opposed to the entire sample collectively, as it would not be appropriate to compare a forward to a defenseman in offensive performance and vice versa in defensive performance. In each EFA, all seven performance metrics were inserted, in which the unweighted least squares method of extraction was applied due to its robustness against non-normally distributed data (Zygmont & Smith, 2014). Furthermore, we applied an oblique rotation as we expected our latent factors to be correlated with one another (Preacher & MacCallum, 2003). Both resulting models passed the Bartlett's test of sphericity ($p<0.001$ in both), and the Kaiser-Meyer-Olkin measure of sampling adequacy (0.659 in forwards and 0.576 in defensemen) (Kaiser, 1974).

Both EFA models retained two latent structures (i.e., factors) with an Eigenvalue of 1.0 or more, which accounted for a cumulative 73% of the variance in forwards and 64% of the variance in defensemen (see Appendix B). The two retained factors were the same for both forwards and defensemen in regard to the variables contained within each one. The first factor includes *P/60, RelFF/60, RelxGF/60,* and *RelGF/60* and was labeled "*Offensive Contribution*". The second includes *RelFA/60, RelxGA/60,* and *RelGA/60* and was labeled "*Defensive Contribution*". It is important to mention that *RelGA/60* had a particularly low communality value (0.170) in defensemen, which necessitated further exploration of its factor loading and importance to the EFA model to decide whether it should be excluded (Costello & Osborne, 2005). Given that (a) this variable had satisfactory factor loading of 0.411 which is above the recommended cut off of 0.32 set by Tabachnick and Fidel (2007), (b) did not cross-load onto other factors in the model, and (c) *RelGA/60* represents goals scored against one's team and, therefore, has conceptual importance to defensive performance, this variable was retained in the analysis.

Initially, the offensive and defensive contribution scores ranged from negative to positive values, with a mean score of 0. However, these scales were transformed to have a minimum value of 1, and every player who did not play a single NHL game during that five year period was given a score of 0 on both factors. This transformation was conducted to (a) ease the interpretation of scores which previously had negative values and an average of 0, and (b) to avoid sampling bias and skewing the analysis by excluding those that did not play, who formed approximately 56% of our sample. Similar procedures are commonly applied in hockey research for the purpose of completeness (Schuckers & Argeris, 2015; Schuckers, 2016). Subsequently, we now have two scales for each playing position measuring offensive and defensive contribution, with a minimum score of 0.

Analysis

A non-parametric approach was chosen in this study due to violations of the normality and homogeneity of variance assumptions for both measures of performance. In order to test the accuracy of draft selection, both offensive and defensive contribution scores were compared across draft rounds using the Kruskal-Wallis *H* test. Epsilon-squared was calculated and reported as a measure of effect size. As for post-hoc analyses, Mann-Whitney U tests with Bonferroni correction (adjusted α value of 0.008) were used to test for differences between successive rounds (i.e., round 1 vs 2, round 2 vs 3, and so on). Mann-Whitney U tests were also used to compare performance between players drafted with lottery picks (#1-14) and non-lottery picks (#15-30).[6] In both cases, correlation coefficients (r) were calculated and reported as a measure of effect size. This particular measure is commonly suggested for the Mann-Whitney U test (Field, 2009; Mangiafico, 2016; Tomczak & Tomczak, 2014), as it relies on the Z-score obtained from the test statistic to produce an easily interpretable measure (Rosenthal, 1991). Again, all above-mentioned tests were carried out for forwards and defensemen separately. Lastly, similar to approaches used by prior research on draft accuracy (Koz et al., 2012), statistical significance was used as the primary threshold for identifying accurate versus inaccurate selection while effect size was a secondary threshold to supplement the interpretation of results.

[6] Note that this number of teams was prior to the introduction of the Vegas Golden Knights in the 2017-2018 NHL season

Results

Forwards

The round in which forwards were selected had a significant, relatively strong, effect on future offensive contribution, $H(6) = 292.051$, $p<0.01$, $\varepsilon^2 = 0.31$. Subsequent post-hoc tests revealed a significant difference with a medium effect size between the 1st and 2nd rounds, and a significant difference with a small effect size between the 2nd and 3rd round. However, all further comparisons showed small, non-significant effects (see Table 1).

Similarly, draft round had a relatively strong, significant effect on future defensive contribution, $H(6) = 219.502$, $p<0.01$, $\varepsilon^2 = 0.23$. Post-hoc comparisons showed a significant difference between the 1st and 2nd rounds with a small effect size, and the same result between the 2nd and 3rd rounds (see Table 1). On the other hand, non-significant differences with weak effect sizes were observed for all the subsequent comparisons.

Defensemen

For defensemen, draft round had a significant, relatively strong, effect on future offensive performance, $H(6) = 173.329$, $p<0.01$, $\varepsilon^2 = 0.31$. Furthermore, post-hoc tests showed a significant difference with a medium effect size between the 1st and 2nd rounds, while all other inter-round comparisons revealed non-significant differences with small effect sizes (Table 1).

Likewise, the round in which defensemen were drafted had a significant, relatively strong, effect on future defensive performance, $H(6) = 145.589$, $p<0.01$, $\varepsilon^2 = 0.26$. However, the only significant difference with a medium effect size was shown between the 1st and 2nd round, while all other subsequent comparisons yielded non-significant results with small effect sizes (Table 1).

Table 1. Inter-round post-hoc comparisons in NHL forwards and defensemen

	Forwards		Defensemen	
Draft round comparison	**Significance level (*p*)**	**Effect size (*r*)**	**Significance level (*p*)**	**Effect size (*r*)**
Offensive performance				
1st vs 2nd	<0.001*	-0.40	<0.001*	-0.46
2nd vs 3rd	<0.001*	-0.23	0.03	-0.15
3rd vs 4th	0.19	-0.05	0.07	-0.12
4th vs 5th	0.04	-0.10	0.32	-0.03
5th vs 6th	0.49	-0.0003	0.38	-0.02
6th vs 7th	0.01	-0.13	0.24	-0.06
Defensive performance				
1st vs 2nd	<0.001*	-0.18	<0.001*	-0.43
2nd vs 3rd	<0.001*	-0.21	0.10	-0.10
3rd vs 4th	0.12	-0.07	0.04	-0.14
4th vs 5th	0.07	-0.09	0.34	-0.03
5th vs 6th	0.49	-0.001	0.45	-0.01
6th vs 7th	0.01	-0.13	0.21	-0.06

*statistically significant at α=0.008

Lottery vs. non-lottery

In our sample of NHL forwards, there was a significant difference in offensive performance with a medium effect size between players drafted with lottery picks (#1-14) and non-lottery picks (#15-30), U = 1523, z = -5.104, p<0.01, r = -0.41. However, forwards did not differ in their defensive performance, U = 2740, z = -0.670, p = 0.25, r = -0.05. As for defensemen, those selected with lottery picks did not differ from their non-lottery peers in either offensive (U = 777.5, z = -0.174, p = 0.43, r = -0.02), nor defensive performance (U = 795.5, z = 0, p = 0.50, r = 0).

Discussion

The purpose of this paper was to assess the accuracy of talent selection across all seven rounds of the NHL draft, as well as examine whether lottery draftees outperform their non-lottery peers within the first round. Results regarding our first purpose showed that projecting future performance of NHL forwards – both offensively and defensively – tended to be accurate in the first two rounds of the draft but began to diminish from that point onwards. On the other hand, defensemen's offensive and defensive performance was projected relatively accurately in the first round, but not in the remainder of the draft. It is evident from both our research, and previous studies (Koz et al., 2012; Shoniker, 2015; Tingling, 2017), that talent selection in the NHL draft is not a linear process in which pick number and future performance are inversely proportional. There was some evidence that such a relationship exists in the beginning of the draft, where the pool of players is still large and heterogeneous enough to be able to distinguish between those who are more likely to become NHL players (i.e., the elite of the elite) and those who are less likely to. However, after a certain inflection point in the draft – which appears to occur between the second and third rounds – identifying true NHL-caliber players becomes increasingly more inaccurate, arguably because the pool of available players becomes homogenous in perceived potential. This homogeneity means that any distinguishing factors between players in rounds 3-7 are more difficult to pinpoint, thus increasing the uncertainty under which NHL decision makers operate.

As for our secondary purpose of evaluating talent selection in the first round, forwards drafted within the first 15 picks (i.e., lottery picks) generally outperformed their counterparts selected with picks #15-30 in offensive performance, but not in defensive performance. These findings reinforce the idea that, generally speaking, forwards in the top of the draft are accurately identified, and that there are clear separating factors not only between first round draftees and the rest of the draft, but also within this elite subgroup itself. For defensemen, however, no differences were observed between lottery and non-lottery picks. Our results show that while defensemen drafted in the first round do, in fact, outperform defensemen in other rounds, the order of selection within the first round itself is not optimal. These findings are consistent with prior analysis by Duroux (2014) who found selection accuracy to be more imprecise in defensemen compared to forwards in the first 30 picks of the draft. They are also consistent with the general conception that projecting future performance of defensemen is more challenging, and less accurate, than that of forwards. From conversations with various NHL scouts, Chang (2011) reported that scouts face more difficulty in assessing the potential of defensemen because many facets of their performance are not yet developed at 18 years of age. Scouts added that much of a defenseman's potential depends on his long-term post-draft development, which occurs in the minor leagues. In forecasting terms, this means that the forecast horizon (i.e., duration between making a forecast and finding the outcome) for a defenseman is considerably longer than that of a forward. This is in accordance with the forecasting literature, which denotes a clear negative effect of the length of forecasting horizon on prediction accuracy (Smith & Sincich, 1991; Swets, 1988). This may also explain why projecting the offensive and defensive performance of defensemen plateaus one round earlier than forwards in our results. A final plausible explanation for these findings is that, generally speaking, defensive performance is more difficult to capture and interpret than offensive performance (Nandakumar & Jensen, 2019; Stimson & Cane, 2017). especially at the amateur level (i.e., junior and collegiate leagues) in which advanced performance metrics are not abundantly recorded and released. This, in turn, makes it more difficult for scouts to identify quality defensemen and project their potential in the NHL compared to forwards.

Implications

The findings of this study have important implications for researchers in this area. First, considering that NHL teams are able to accurately predict future performance in the beginning of the draft, but have less success doing so from the third round onwards, researchers could benefit from identifying unique predictors of NHL success that exist in different portions of the draft (e.g., rounds 1-2 vs. 3-7, or top half of the draft vs. bottom half). Such analysis may shed more light on variables that distinguish future performers in later rounds among such a seemingly homogenous group of athletes. Second, we suggest more emphasis should be placed on identifying the particular decision making errors that teams commit while drafting. For example, Berri and Simmons (2011) found that NFL scouts value height, 40-yard dash time, and Wonderlic test scores[7] when drafting quarterbacks, yet these variables were shown to have minimal relation to future success. Similar examination in hockey is needed to reveal which variables are overvalued, or undervalued, by NHL scouts in order to make informed corrections to current practices. Third, given the low selection accuracy found in our results, combined with prior indications by scouts that defensemen take longer to develop after being drafted (Chang, 2011), we suggest future research might benefit from studying *post-draft predictors* of NHL success for defensemen; particularly, during their developmental years in the minor league systems. Examples of post-draft predictors may include the duration of time spent in the minor leagues after being drafted, amount of playing time given per game, the nature of assignments given to the player on the ice (e.g., power-play, penalty kill, quality of competition, etc.), the number of times a player is called up to the NHL, among many more. Such research is necessary to guide appropriate talent development practices past the point of selection.

As for practical implications of our findings for practitioners, first, we suggest that in order to improve selection accuracy – particularly in the later rounds – NHL teams should broaden the scope of the information they collect on prospects beyond traditional performance

[7] The Wonderlic test – named after psychologist Eldon Wonderlic – is a test of cognitive ability and problem solving skills, which is administered to draft-eligible players prior to the NFL draft (Berri & Simmons, 2011).

metrics and physical test scores. For instance, scouts may benefit from collecting information on some psychological characteristics such as resilience and competitive anxiety management (Galli & Gonzalez, 2015; Neil et al., 2012), which have been shown to be differentiating attributes between expertise levels in sport (see Jordet [2015] for a review). In addition, other characteristics, such as motivational levels and self-regulation, have been identified as important predictors of performance over time (Gillet et al., 2009, 2012; Jonker et al., 2012). Indeed, integrating psychological characteristics in selection models is often met by the limitations of self-reported questionnaires (Brenner & DeLamater, 2016); however, there are some alternative approaches that teams may benefit from. For instance, Musculus and Lobinger (2018) recommend the collaboration of sport psychologists and scouts to formulate assessment tools (e.g., evaluation sheets) containing important psychological characteristics, and identifying anchor behaviors associated with each characteristic. Such assessment tools can then be used to collect data on players through interviews as well as behavioral observations (via video analysis or in person). To ensure the validity of such measurements, the aforementioned characteristics should be linked to future performance using empirical analyses and scouts' intuitive knowledge. Similarly, to optimize reliability, the authors recommend that the number of items used to assess each characteristic should be maximized, and that more than one scout should conduct the assessment to achieve inter-rater reliability (Musculus & Lobinger, 2018).

Second, although some of the aforementioned factors that offset selection accuracy – such as the length of forecast horizon for defensemen and homogeneity of perceived talent in later rounds – are inherent systematic constraints that are outside of the decision makers' control, selection inaccuracy can also be partly attributed to certain irrationalities committed by decision makers in the draft. Therefore, teams may benefit from educating their scouts – through workshops and other methods – on cognitive biases that impact their decision making processes and how to minimize their impact on player evaluation. Examples of such biases include confirmation bias (Nickerson, 1998), primacy effect (Boywitt & Brandt, 2012; DiGirolamo & Hintzman, 1997), recency bias (Kalm & Norris, 2018; Trotman & Wright, 2000), among many more. All of which have been linked to poor talent evaluation by coaches and experts in various sports settings (Greenlees et al., 2007; Johnston & Baker, 2020; Smith et al., 2009; Sobczyk & Parzelski, 2015).

Limitations

While this study extends our understanding of draft selection in the NHL, there were limitations in our design. First, although the advanced metrics used in this study offer a comprehensive view of players' tangible on-ice performance, they do not take into consideration their intangible contributions – whether on or off the ice – towards their teams (e.g., leadership qualities, being a good teammate, etc.). Second, we used data from players' first five seasons post draft to capture performance. Although the percentage of players who have not played a single NHL game in the first five years (56%) is very similar to the percentage of those who did not play ever (58% as shown by Tingling [2017]), our analysis may limit the inclusion of any potential "late bloomers". Our understanding of players who join the professional league later than average is particularly limited and provides an interesting avenue for further research. Third, the two latent factors from our EFA models accounted for 73% and 64% of the variance in the data in forwards and defensemen, respectively. This means that there is a portion of players' offensive and defensive contributions that remain unaccounted for in this analysis. However, this is a limitation of hockey analytics in general, as the NHL lacks a universally accepted "catch all" performance metric such as Wins Above Replacement (WAR) in baseball or Player Efficiency Rating (PER) in basketball.

Perspective

Talent identification and selection in the draft is crucial to the long-term success of an NHL organization. It is also one of the most challenging aspects of hockey operations, as it involves forecasting the future performance of draft-eligible players under a great degree of uncertainty. Our results show that the accuracy of draft selections in the NHL is limited to the first two rounds, with very low accuracy in the remaining rounds of the draft. We also find that forwards selected with lottery picks outperform those selected with non-lottery picks, but this effect was not shown in defensemen. While there are several factors that could explain these effects, future research is necessary to further explore the mechanisms that lead to draft inefficiencies, possibly by testing for implicit cognitive biases effects that may affect the quality of decision making, as well as greater exploration of the performance metrics and physical attributes that NHL decision makers overvalue, or undervalue, in the draft.

Chapter Three

Diamonds in the rough: Using text-mining to identify inefficiencies in the National Hockey League Draft

Abstract

Making accurate draft selections is essential for the long-term success of an NHL organization, particularly under the current financial restrictions imposed by the salary cap. Yet, recent research has shown that the NHL draft involves a great degree of uncertainty, and that teams' ability to project future performance is rather limited. The specific underlying inefficiencies, however, remain understudied. To address this gap, this study aimed to (a) determine the predictors of NHL draft order, and (b) assess how such predictors fare in projecting players' future NHL success. Such predictors include various on-ice metrics, anthropometric measures, and subjective qualities extracted from text-mined scouting reports. Results showed that forwards' penalty minutes, height, age, and lack of physical strength were overvalued in the draft, while plus/minus, board battles, backchecking ability, and hockey sense were undervalued. As for defensemen, NHL teams overvalued CSB rankings, and undervalued playmaking ability, lack of physical strength, and work ethic/leadership. In addition to highlighting draft inefficiencies, this study offers numerous practical and research-based suggestions that could lead to enhanced selection efficiency in the NHL.

Introduction

In the aftermath of the 2005 labor disruption (i.e., lockout), the National Hockey League (NHL) implemented a salary cap, setting a limit on the total amount of salaries that teams can pay their players in a single season (Yoost, 2006). As a result of this newly implemented policy, the competitive balance in the league began to rise gradually, as wealthy teams were no longer able to monopolize star players whom other teams could not afford. Today, the parity in the NHL surpasses that of any other major North American league (Rockerbie, 2016).

In this highly competitive, salary restricted environment, it has become more important than ever to draft accurately (Silverman, 2013), since rookies are signed to Entry Level Contracts (ELC) that cost much less than those of veteran players. Not to mention that after the duration of ELCs, teams have exclusive negotiation rights with their draftees during a period known as Restricted Free Agency (RFA). Having exclusive negotiation rights means teams hold much of the leverage in signing their own draftees to favorable contracts, as no other team is able to outbid them. Therefore, by making the right selections at the draft, teams can retain productive players for multiple years under cost certainty, and earn a competitive advantage over other teams that do not draft well.

Despite the importance of making accurate selections on long-term success, research has shown that the draft suffers from substantial inaccuracies. For instance, Koz et al. (2012) reported non-significant differences in NHL games played between rounds three, four and six, indicating that draft order is not associated with career length in these rounds. In addition, the authors found that those drafted in round 6 accumulated more NHL games than players selected before them in round 5. Similarly, Farah and Baker (2020) conducted retrospective analyses comparing NHL offensive and defensive performance across draft rounds. Their results showed that forwards and defensemen drafted in rounds 3-7 did not differ significantly in their on-ice contributions. Findings from both studies suggest that teams' ability to distinguish future performers is inadequate past the first two rounds, and that there are many "misses" in the draft, wherein players selected with later picks end up outperforming their counterparts selected before them.

These selection inaccuracies have led researchers to develop models that outperform NHL teams in finding talent through the draft. For example, Schuckers (2016) constructed a generalized additive model using height, weight, pre-draft performance metrics and Central Scouting rankings, which outperformed draft order in predicting NHL games played by 20%. Likewise, Seppa et al.'s (2017) model of the same variables – with the addition of text-mined scouting reports – outperformed NHL draft order in predicting prospects' American Hockey League (AHL) performance by 22%. While such studies indicate there is considerable room for improvement in the draft, they do not highlight the exact inefficiencies involved in selection. Furthermore, they leave unanswered questions as to which variables are over or undervalued by NHL teams, and which adjustments need to be made to their talent evaluation processes.

To that end, the purpose of this research was to explore inefficiencies in the draft by determining the predictors of draft order (part #1), and assessing how such predictors fare in projecting future NHL performance (part #2), by using a variety of on-ice metrics as well as text-mined scouting reports.

Methods

Sample

The sample included all forwards (N = 825) and defensemen (N = 498) drafted into the NHL from 2008-2014 (total N = 1323). This particular sample was chosen as scouting reports for draftees prior to 2008 were not available for data collection. Moreover, 2014 was used as a cut-off point to allow a five-year window of subsequent NHL performance to be collected.

Independent variables – quantitative data

Table 1 displays the independent variables used in this study, along with a brief description of each. The rationale and theoretical reasoning for collecting these variables is detailed below.

Table 1. Quantitative independent variables used to predict draft order (part #1) and subsequent NHL performance (part #2)

Independent variable	Definition
NHL Equivalency Points Per Game (NHLe PPG)	The rate of the prospect's point scoring per game adjusted for league quality
Penalty Minutes per Game (PIMs/GP)	Total number of penalty minutes accumulated by the prospect
Plus/Minus (+/-)	Difference between goals scored for and against the team while the prospect was on the ice
CESCIN-Adjusted CSB Rankings	Prospect's final CSB ranking before his draft
Age	Prospect's age at the time of his draft (measured in months)
Height	Prospect's height at the time of his draft (measured in inches)
Weight	Prospect's weight at the time of his draft (measured in pounds)

CESCIN = Central Scouting Integrator; CSB = Central Scouting Bureau

Standard performance metrics

Given the scarcity of advanced performance analytics for junior leagues, only standard performance metrics were available. All metrics were collected from eliteprospects.com for each player's final regular season before being drafted. These included *Games Played (GP)* – the number of games played in a player's final season before being drafted. This represents a measure of the sample size available to evaluate a player in his final year; *NHL Equivalency Points Per Game (NHLe PPG)* – a player's scoring rate adjusted for pre-draft league quality (refer to Appendix C for an overview of NHLe methodology); *Penalty Minutes per Game*

(PIMS/GP) – an indicator of two things: (a) a player's on-ice discipline, and (b) a proxy for a player's perceived "toughness", as players who fight more accumulate more penalty minutes; *Plus-Minus (+/-)* – a proxy for a player's defensive contribution, given that it accounts for goals scored for-and-against one's team while a player is on the ice. Although the latter is a flawed measure of defense and has been replaced by other advanced metrics at the NHL level, it is still important to study its influence on draft decisions.

Anthropometric and demographic measures

Players' *height* and *weight* were collected from thedraftanalyst.com. In addition to anthropometric measures, players' *age* (in months) at the time of their draft was collected from hockeydb.com. This variable was included in the analysis since draftees vary in age from late teens to early twenties. Given that certain pre-draft leagues – such as the Ontario Hockey League – have an age range of 16-21, a 17-year-old who scores 50 points may be considered more promising than a 20-year-old who scores at the same rate. Therefore, the influence of this variable on draft decisions seemed important to take into consideration.

Central Scouting Bureau rankings

The Central Scouting Bureau (CSB) is a department housed within the NHL that is independent from any of the 32 member teams. Its purpose is to establish a centralized ranking database for all prospects in a draft class, which can then be utilized by teams to supplement their own independent scouting evaluations. CSB's final rankings, prior to each year's draft, were collected from thedraftanalyst.com.

It is important to note, however, that the CSB releases separate rankings for players competing in North American and European leagues. Therefore, for CSB rankings to be utilized in this analysis, it is necessary to integrate the North American and European lists into one unified ranking. To do so, the Central Scouting Integrator (CESCIN) developed by Fyffe (2011) was used to combine both lists. For an overview of CESCIN methodology, and the coefficients used for North American and European players, please refer to Appendix D.

Independent variables – qualitative data

In addition to the on-ice and anthropometric data detailed above, players' scouting reports were collected from an independent scouting agency that tracks and evaluates draft eligible players. In order to utilize scouting reports in the form of quantitative independent variables, Natural Language Processing (NLP) techniques were applied to text-mine information on players' "intangible" attributes that are not captured by their on-ice metrics.

There are numerous ways to utilize NLP to text-mine scouting reports, one of which is to build "dictionary categories", where each category represents an attribute (e.g., playmaking ability), under which there are two sub-categories that represent whether a player is "good" or "poor" at that attribute. Common words and phrases can then be from text documents, and coded into each sub-category. Subsequently, all players whose reports include that word, or phrase, would be coded as good or poor under each attribute.

Although this approach has been previously used in hockey research (Seppa et al., 2017), it was not deemed fit for the nature of our scouting reports, as coding results showed the data had substantial skewness within each attribute towards one value or another. In other words, the vast majority of – if not all –players under a certain category would belong to either the "good" or the "poor" sub-group. This suggests that certain attributes are only mentioned when they are strengths, and other attributes are only mentioned when they are weaknesses. It is noteworthy that this limitation of scouting data is not exclusive to the reports used in this study, but rather hockey scouting in general, as will be detailed in the discussion section.

In lieu of building dictionary categories, another approach to text-mining – known as Topic Modelling (TM) – was carried out using Wordstat 8.0. This method involves combining NLP with statistical analysis to mine for, and extract, patterns in text documents based on the co-occurrence of certain words and phrases (Péladeau & Elnaz, 2018). The origin of this analysis dates back to the early 1960s, when Borko and Bernick (1963) attempted to automate the classification of text documents in order to explore the latent structures of their content. Since then, thanks to the rapid advancements in technology and automation, TM has become a widely adopted practice in fields where large unstructured texts are common, such as economics (Corbet et al., 2019; Nevzorova et al., 2017; Uğur & Akbıyık, 2020), politics (Fang, 2019; Moodley & Marivate, 2019), social sciences (Mădălina, 2016), and journalism (Jacobi et al., 2016).

In the context of this study, the latent topics of interest were attributes of prospects' performance that were technical (e.g., playmaking ability, defensive positioning, etc.), tactical (e.g., decision-making, play reading, etc.) or psychological (e.g., work ethic, leadership qualities, etc.), and serve as dichotomous independent variables. In almost all cases, attributes were exclusively mentioned in either a positive or negative way, thereby creating dichotomous variables wherein players identified as having a particular attribute – whether good or bad – were coded with "1", and those that were not identified as such were coded with "0". Of course, it is possible that a prospect who was not described as having good work ethic, for instance, does not necessarily have bad worth ethic. However, this method of dichotomous coding was the most appropriate approach given the nature of the reports, and the skewness of the dictionary building results highlighted above.

While there are multiple statistical methods of extracting topics [e.g., Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA), Non-negative Matric Factorization (NMF)]

(Griffiths & Steyvers, 2004; Mcauliffe & Blei, 2008; Onan, 2019) we chose Factor Analysis (FA) to model topics for two main reasons. First, unlike other methods, FA allows for the same word to occur in multiple topics as opposed to only one, which offers a more realistic representation of the polysemy of words and phrases (Mădălina, 2016). This is an important feature for our analysis as some words such as “shot”, for example, are likely to occur in phrases describing offensive abilities (e.g., “player X has an accurate shot”), or defensive abilities (e.g., “player X is willing to block shots”). Second, research has shown topics extracted using FA are more coherent and interpretable to human subjects than ones extracted using other methods, such as LDA (Péladeau & Elnaz, 2018). Given that findings from this research may be of interest to hockey scouts, the interpretability of extracted topics was of considerable importance.

Topic modelling steps

Similar to traditional quantitative FA, topic modelling requires several steps to prepare the textual data for analysis. The following section details such steps, and their relevance to the outcome of the analysis:

1. *Exclusion list* – creating an exclusion list informs the software of words that are uninformative, and therefore not useful, for the analysis. Such uninformative words include pronouns and conjunction words, as well as words that are not descriptive of players’ performance or attributes. The full exclusion list can be seen in Appendix F. This step is important to achieving accurate topic modelling, as without creating an exclusion list, topics may be “diluted” by the presence of uninformative words.
2. *Substitution* – this process involves two steps:
    a- *Automatic spell correction* – this step ensures all misspelled words throughout the text documents are substituted with their correct spelling. Moreover, this

step ensures certain words that are inconsistently spelled as either one-word or two-words (e.g., “stickhandle” or “stick handle”) are transformed into one consistent form of the word.

b- *Lemmatization* – this part of the substitution process groups various inflected forms of a word together, by converting words to their original base form. Specifically, lemmatization transforms plural words into their singular forms, and different verbs into their present-tense forms (e.g., “blocks”, “blocking” and “blocked” would all be captured as “block”). This step helps the software recognize the presence of a word, and its meaning within the context, despite its occurrence in several forms. Despite its value, lemmatization may create errors in some cases for words that, despite having the same base form, do in fact have different meanings. For instance, “improved” was almost always used in a positive way when describing players (e.g., he has improved his defensive play), whereas “improve” was often used in a negative way (e.g., he needs to improve on face offs). Yet, both forms of the word would be captured as “improve”. To counter this potential problem, different forms of each word appearing in extracted topics were checked manually as is described in step #5.

3. *Topic extraction* – after preparing text documents the next step was to extract topics (i.e., player attributes) from the scouting reports. To do so, the following settings were made in Wordstat 8.0:

a- *Segmentation* – this controls whether extracted topics are based on the co-occurrence of words in the same document (i.e., entire scouting report), paragraph, or sentence. Given that our purpose was to extract numerous attributes of players (i.e., as opposed to one general theme across a document or a paragraph), the option of segmenting by sentence was chosen.

b- *Loading* – this determines the minimum loading of a word or phrase onto its topic. The general guidelines for TM loadings are similar to that of quantitative FA, in which 0.20 – 0.30 is generally considered an acceptable cut-off point (Borko & Bernick, 1963; Iker, 1974; Péladeau & Elnaz, 2018). Subsequently, 0.30 was used as a minimum cut-off for factor loading in this analysis.

4. *Topic retainment* – after topic extraction was performed, the number of topics to retain was determined based on selection criteria in the following order:

a- *Eigenvalue* – factors with an eigenvalue of 1 or higher are generally recommended to be retained (Kaiser, 1960; Kanyongo, 2006; Kruder & Richardson, 1937). In our analysis, all extracted topics had an eigenvalue above that threshold, and therefore met this criterion for retainment. It is important to mention that the plotted eigenvalues (i.e., scree plot shown in Appendix G), did not present a definite inflection point. Therefore, it could not be used to determine factor retainment (Field, 2009; Woods & Edwards, 2011).

b- *Interpretability and relevance* – as previously mentioned, the purpose of TM was to extract topics that represent attributes of draft eligible players, as opposed to general – or abstract – hockey related concepts. Therefore, it was important to distinguish which category a topic fell under in order to retain or discard it. To do so, the "keyword in context" feature was used to retrieve all cases (i.e., players) whose reports included each topic, along with the context in which topic keywords were used. For a topic to be retained, it had to be mentioned in a descriptive manner regarding players' performance in at least 80% of the cases. Furthermore, the direction of the topic used to describe players (i.e., positive or negative connotation) had to be consistent in at least 80% of the cases. Both of these rules were adopted from prior text mining literature (Ermakov & Ermakova, 2013; Humphreys, 2019; Humphreys & Wang, 2018). In total, 10 topics did not fit these criteria and were therefore discarded.

5. *Case filtering* – the final step was to ensure all cases listed under each topic were in fact accurately coded. This step was important since topics are extracted based on the co-occurrence of certain keywords – or phrases – in the same sentence, meaning that there is a small chance certain cases were accidentally coded under a topic due to coincidentally having such keywords, but not within the actual context of the topic. To ensure the accuracy of coding, every case under each topic was manually checked for accuracy using the "keyword in context" feature. Cases that were accidentally coded were removed.

After the above-mentioned steps were followed, 13 topics (i.e., attributes) were ultimately retained and used as independent variables in our regression analyses. Table 2 presents these topics along with their definitions, as many of them include technical hockey terminology. Again, the dichotomous coding of each independent variable consisted of giving a player a value of 1 if he was described as having that attribute, and a value of 0 if he was not.

Table 2. Text-mined independent variables used to predict draft order (part #1) and subsequent NHL performance (part #2)

Independent variable	Keywords and phrases	Definition	Connotation	Eigenvalue
Backchecking ability	Backcheck; back; come; defensively; comes back; deep into his own zone; comes back deep	A player's willingness, and ability, to backtrack from the offensive zone and prevent scoring chances against his team	Positive	1.6
Board battles	Along; wall; board; battle; along the wall; battles along the wall; hard along; hard along the wall; game along the wall; along the boards; puck along	A player's ability to "battle" for the puck along the boards in order to gain possession of it	Positive	2.69
Defensive awareness	Gap; lane; active; position; stick; control; maintain; active stick; gap control	A player's overall awareness in his own defensive zone. Including how he positions himself and how he uses his stick to suppress chances against	Positive	2.29
Hockey sense	Hockey; hockey sense; good hockey sense; has good hockey sense; vision and hockey sense; hockey sense and smarts	A common term in hockey used to describe a player's decision-making ability and overall intelligence	Positive	1.97
Passing and playmaking ability	Pass; make; crisp; outlet; ice; see; vision; playmaker; distribute; outlet pass; see the ice; make a solid; strong outlet; breakout pass; strong outlet pass' solid first	A player's ability to make good passes and create scoring chances via playmaking for his team	Positive	3.03

	pass; accurate pass; crisp pass; make a good first pass			
Puck protection ability	Puck; poise; protect; puck skills; protect the puck; carry the puck; puck on his stick; handle the puck; can handle the puck; protects the puck; puck protection; solid puck; take the puck; creative with the puck; get the puck; has the puck; puck battles; puck carrier	A player’s ability to shield the puck from the opposition and maintain possession of it despite pressure	Positive	1.55
Shooting ability	Shoot; release; wrist; velocity; accurate; quick; accuracy; slap; wrist short; quick release; has a quick; accurate shot; has a quick release; wrist shot with a quick; deceptive release; hard wrist shot; shoot the puck	A player’s ability to shoot the puck efficiently, based on velocity and accuracy	Positive	2.48
Shot blocking ability	Block; shot; lane; slap shot; block a shot	A player’s anticipation of opposition’s shots and willingness to block them	Positive	1.56
Soft hands	Hand; soft; vision; beat; one-on-one; defender; beat defenders; can beat defenders; can beat defenders one-on-one	A common term in hockey used to describe a player’s stickhandling skill, and his ability to use stick moves to evade a defender	Positive	1.92
Willingness to fight	Drop; gloves; will; fight; stick up; drop the gloves; will drop the gloves; will stick up	A player’s willingness to defend his teammates by engaging in a fistfight	Positive	2.11

Work ethic and leadership	Leadership; leader; work; ethic; quality; work ethic and leadership	A player's perceived intrinsic motivation to work hard during games and lead his team	Positive	1.58
Inconsistency in effort and performance	Effort; level; consistency; shift; effort level; shift to shift; would like to see	Fluctuations in a player's perceived effort output, and overall performance, from shift to shift	Negative	1.82
Lack of physical strength	Add; strength; need; muscle; frame; considerable; leg; needs to add; will need; add strength; needs to add strength; will need to add; add considerable; add considerable strength; needs to add more strength	A player's perceived lack of lower-and-upper body strength	Negative	2.18

Dependent variables

In part 1 of the study, whose purpose was to determine predictors of selection order, the dependent variable was *draft pick number*. For part 2, which explored predictors of subsequent performance, the dependent variable was number of *NHL games played*.

Analysis

Part 1

To determine the predictors of NHL draft order, a multiple linear regression analysis was conducted using SPSS, in which draft pick number was regressed on all independent variables shown in Tables 1 and 2. This analysis was performed independently for forwards and defensemen, as scouts' evaluation of each position was expected to vary based on their differing demands.

Unstandardized beta coefficients, significance, 95% confidence intervals, and semi-partial correlations were calculated and reported for each analysis.

As for model diagnostics, the assumptions of normality, homoscedasticity, and linearity were successfully met in both forwards and defensemen using histograms, standardized predicted values versus standardized residual plots, and partial regression plots, respectively. In addition, the assumption of no multicollinearity [forward sample: mean variance inflation factor (VIF) = 1.27, VIF range = 1.05 – 1.81; defensemen sample: mean VIF = 1.24, VIF range = 1.06 – 1.92] was substantiated. Similarly, the assumption of independent errors was met [forward sample: Durbin-Watson (D-W) statistic = 2.05; defensemen sample: D-W = 1.81]. Lastly, post-hoc power analyses yielded a power of 0.99 and 0.92 for forwards and defensemen samples, respectively.

Part 2

To determine the predictors of NHL success, a Zero-Inflated Negative Binomial (ZINB) regression was conducted, wherein the number of NHL games played was the dependent variable, and the independent variables displayed in Table 1 were the predictor variables. ZINB regression was most suitable for the nature of our data for two reasons: first, it accounts for excess values of zero in the outcome variable (NHL GP), which is the case for most NHL draftees. In fact, 68% of forwards and 74% of defensemen did not play a single NHL game (see Appendix E for distribution plots). It is important to note that while a Zero-Inflated Poisson (ZIP) regression may also be used in similar instances of zero inflation, the vast discrepancy between the mean and variance (i.e., over-dispersion) in the outcome variable [forwards: mean = 17.77, variance = 1935.69; defensemen: mean = 35.02, variance = 5280.65] make ZINB a more suitable option (Minami et al., 2007).

Second, ZINB operates under an assumption that zero values come from two different sources: (a) “certain” zeros, which are fixed at that value, and (b) values that “happen to be zero”, but could in theory take other values (Ridout et al., 2001). In our case, certain zeros are draftees who simply do not perform well enough to earn an NHL roster spot, while values that happen to be zeros are draftees who have not played an NHL game due to other reasons. Some of those reasons may be injuries, a player performing well enough to play in the NHL but his team does not have vacancies, or simply those that have not played *yet* in their first five years but may play at a later time. Therefore, using ZINB allows us to acknowledge that not all draft picks who played 0 games within five years were inaccurate, or unsuccessful, picks; rather, there is a portion of whom that did not play for other reasons as well.

Given that there are two theoretical sources of zero values at play, ZINB regression produces two partial models in its analysis. The first is called a *zero-inflated model*, which is concerned only with zero values, and uses a logit function (i.e., logistic regression) to predict whether such values are “certain zeros”. The second is a *count model*, which removes all certain zeros, and uses a negative binomial regression to predict non-certain zeros and values ≥ 1. For each model, regression coefficients, Z-values, and *p*-values were calculated and reported.

To measure the effect sizes of independent variables, Odds Ratio (OR) was used in the zero-inflated model by exponentiating the regression coefficients ($OR = e^{\beta}$, where β is the regression coefficient). This was done given the relevance of OR in logistic regression and its ease of interpretability in cases of binary outcomes (Szumilas, 2010). As for the negative binomial regression (i.e., count model), the effect size reported was Incidence Risk Ratio (IRR), and it is important to mention why it was derived, and how it can be interpreted within the specific context of this study. Negative binomial regression coefficients (β) resemble the difference between the logs of expected NHL games (μ) given a one-unit increase in the independent variable (x): $\beta = \log(\mu_{0+1}) - \log(\mu_0)$. Considering that the difference between the log counts of NHL games highlighted above is equal to the log of the quotient $[\log(\mu_{0+1} / \mu_0)]$, the regression coefficient can be interpreted as a "ratio". Moreover, given that we are evaluating NHL success during the first five years post draft, the dependent variable is in itself a "rate" (i.e., games played over the first five years post draft). Therefore, the regression coefficient also represents the log of the rate ratio, and the rate at which NHL games accumulate is an "incidence rate". Therefore, by exponentiating the regression coefficient (e^{β}), the IRR of NHL games can be derived and interpreted as such.

Results – Part 1

This section presents the findings of the multiple linear regression analyses used to predict NHL draft order. Results pertaining to forwards and defensemen are presented separately, each containing descriptive statistics, correlation coefficients, as well as the regression model summary.

Forwards

Table 3 displays the descriptive statistics for the independent and dependent variables in the forwards' sample (N = 385). For correlation coefficients between all variables, please refer to Appendix H – Table H1. For the regression analysis, the overall model was a significant predictor of NHL draft order: F (21, 363) = 10.36, $p < 0.01$, $R^2 = 0.375$. As displayed in Table 4, eight of the 21 independent variables were significant predictors of forwards' draft order; namely CSB ranking, height, age, GP, NHLe PPG, PIMs/GP, passing and playmaking ability, and lack of physical strength. In terms of effect sizes, absolute semi-partial correlation values ranged from 0.08 to 0.30 in those eight variables, suggesting small-moderate effects on draft order, with

NHLe PPG having the biggest effect on selection number. Moreover, of the significant variables, CSB ranking, age, and GP were directly proportional to draft order, wherein an increase in these values resulted in players being drafted later. On the other hand, the five remaining variables were inversely proportional to draft order, wherein an increase in their values resulted in earlier selection of forwards. In regard to non-significant predictor variables, only the ability to block shots was close to significance with a *p* of 0.064, and a negative beta coefficient suggesting this attribute led to earlier selection. All other non-significant predictors had very low semi-partial correlation values, indicating trivial effects on draft order.

Table 3. Descriptive statistics of the independent and dependent variables in the forwards' sample

Variable	Mean	Standard deviation
Draft pick number	70.86	53.68
CESCIN-adjusted CSB ranking	106.19	223.64
Height	72.30	1.85
Weight	186.50	14.73
Age	220.07	5.38
GP	51.44	20.24
NHLe PPG	0.24	0.11
PIMs/GP	0.79	0.65
Plus/minus	6.08	16.29
Shot blocking ability	0.09	0.29
Defensive awareness	0.19	0.39
Puck protection ability	0.27	0.44
Board battles	0.28	0.45
Work ethic and leadership	0.30	0.46
Willingness to fight	0.13	0.33
Soft hands	0.48	0.50
Shooting ability	0.67	0.47
Passing and playmaking ability	0.68	0.47
Lack of physical strength	0.36	0.48
Inconsistency in effort and performance	0.28	0.45
Hockey sense	0.22	0.42
Backchecking ability	0.17	0.37

CESCIN = Central Scouting Integrator; CSB = Central Scouting Bureau; GP = Games Played; NHLe PPG = National Hockey League Equivalency Points Per Game; PIMs = Penalty Minutes

Table 4. Multiple regression analysis of NHL draft order in the forwards' sample

Variable	Unstandardized beta coefficient (β)	t	95% confidence interval	Semi-partial correlation
Constant	71.27	0.48	-219.30 – 361.84	
CESCIN-adjusted CSB ranking	0.07**	5.95	0.05 – 0.09	0.25
Height	-5.02**	-3.13	-8.17 – -1.86	-0.13
Weight	0.08	0.41	-0.32 – 0.48	0.02
Age (months)	1.83**	3.89	0.91 – 2.76	0.16
GP	0.30*	2.31	0.04 – 0.56	0.10
NHLe PPG	-186.12**	-7.13	-237.46 – -134.84	-0.30
PIMs/GP	-7.99*	-2.01	-15.81 – -0.16	-0.08
Plus/minus (+/-)	-0.19	-1.23	-0.48 – 0.11	-0.05
Shot blocking ability	-15.23	-1.86	-31.36 – 0.89	-0.08
Defensive awareness	1.51	0.25	-10.53 – 13.50	0.01
Puck protection ability	-1.48	-0.28	-12.09 – 9.13	-0.01
Board battles	-8.01	-1.54	-18.28 – 2.25	-0.06
Work ethic & leadership	-4.43	-0.87	-14.41 – 5.54	-0.04
Willingness to fight	-8.78	-1.22	-22.94 – 5.38	-0.05
Soft hands	-4.17	-0.89	-13.33 – 4.99	-0.04
Shooting ability	-1.91	-0.39	-11.51 – 7.69	-0.02
Passing & playmaking ability	-12.68*	-2.40	-23.07 – -2.29	-0.10
Lack of physical strength	-10.10*	-1.99	-20.05 – -0.15	-0.08
Inconsistency in effort & performance	-3.39	-0.64	-13.87 – 7.08	-0.03
Hockey sense	-7.81	-1.39	-18.83 – 3.20	-0.06
Backchecking ability	-8.81	-1.42	-21.02 – 3.41	-0.06

CESCIN = Central Scouting Integrator; CSB = Central Scouting Bureau; GP = Games Played; NHLe PPG = National Hockey League Equivalency Points Per Game; PIMs = Penalty Minutes; *$p < 0.05$; **$p < 0.001$

Defensemen

Table 5 displays the descriptive statistics for the independent and dependent variables in the Defensemen's sample (N = 204). For correlation coefficients between all variables, please refer to Appendix H – Table H2.

Table 5. Descriptive statistics of the independent and dependent variables in the defensemen's sample

Variable	Mean	Standard deviation
Draft pick number	69.72	54.60
CESCIN-adjusted CSB ranking	91.26	160.03
Height	73.55	1.95
Weight	192.37	14.49
Age	219.94	4.84
GP	51.06	18.94
NHLe PPG	0.14	0.08
PIMs/GP	0.99	0.64
Plus/minus	7.10	17.50
Shot blocking ability	0.11	0.31
Defensive awareness	0.59	0.49
Puck protection ability	0.27	0.44
Board battles	0.25	0.44
Work ethic and leadership	0.18	0.39
Willingness to fight	0.13	0.33
Soft hands	0.14	0.35
Shooting ability	0.51	0.50
Passing and playmaking ability	0.82	0.38
Lack of physical strength	0.32	0.47
Inconsistency in effort and performance	0.14	0.34
Hockey sense	0.09	0.29
Backchecking ability	0.02	0.16

CESCIN = Central Scouting Integrator; CSB = Central Scouting Bureau; GP = Games Played; NHLe PPG = National Hockey League Equivalency Points Per Game; PIMs = Penalty Minutes

The regression model was found to significantly predict draft order: F (21, 182) = 5.91, $p < 0.01$, $R^2 = 0.406$. As displayed in Table 6, four independent variables were significant predictors: CSB ranking, height, NHLe PPG, and plus/minus. In terms of their individual predictive validity, absolute semi-partial correlation values ranged from 0.13 to 0.32, indicating small-medium sized effect. Among the significant variables, height, NHLe PPG, and plus/minus were inversely related to draft order, suggesting an increase in these values lead to earlier draft selection in defensemen. On the other hand, CSB ranking was directly proportional to the outcome variable, indicating an opposite relationship.

It is noteworthy that none of the independent variables extracted from scouting reports were significant predictors of draft order; however, puck protection ability neared significance with a *p* value of 0.07. All other non-significant predictors showed very small semi-partial correlation values, indicating their trivial effects on draft order in defensemen.

Table 6. Multiple regression analysis of NHL draft order in the defensemen's sample

Variable	Unstandardized beta coefficient (β)	t	95% confidence interval	Semi-partial correlation
Constant	493.68*	2.41	89.89 – 897.47	
CESCIN-adjusted CSB ranking	0.10**	5.01	0.06 – 0.14	0.29
Height	-8.73**	-4.07	-12.97 – -4.49	-0.23
Weight	-0.03	-0.09	-0.62 – 0.56	-0.01
Age (months)	1.20	1.78	-0.13 – 2.53	0.10
GP	0.23	1.22	-0.14 – 0.59	0.07
NHLe PPG	-276.61**	-5.64	-373.36 – -179.86	-0.32
PIMs/GP	-7.84	-1.45	-18.46 – 2.79	-0.08
Plus/minus (+/-)	-0.45*	-2.33	-0.83 – -0.07	-0.13
Shot blocking ability	-13.44	-1.26	-34.52 – 7.64	-0.07
Defensive awareness	0.37	0.06	-12.85 – 13.59	0.00
Puck protection ability	-13.86	-1.84	-28.71 – 0.99	-0.11
Board battles	-0.13	-0.02	-15.11 – 14.86	0.00
Work ethic & leadership	-9.29	-1.04	-26.88 – 8.30	-0.06
Willingness to fight	-14.50	-1.44	-34.34 – 5.33	-0.08
Soft hands	-5.69	-0.61	-24.16 – 12.78	-0.03
Shooting ability	4.01	0.60	-9.12 – 17.14	0.03
Passing & playmaking ability	-8.41	-0.96	-25.61 – 8.79	-0.06
Lack of physical strength	4.25	0.56	-10.66 – 19.16	0.03
Inconsistency in effort & performance	-5.08	-0.53	-23.97 – 13.82	-0.03
Hockey sense	9.59	0.87	-12.16 – 31.34	0.05
Backchecking ability	-12.04	-0.57	-52.37 – 29.30	-0.03

CESCIN = Central Scouting Integrator; CSB = Central Scouting Bureau; GP = Games Played; NHLe PPG = National Hockey League Equivalency Points Per Game; PIMs = Penalty Minutes; $*p < 0.05$; $**p < 0.001$

Results – Part 2

As mentioned in the analysis section, ZINB produces a two-part model to predict the outcome variable. One is known as a zero-inflation model, which predicts the likelihood of playing zero NHL games, while the other is a count model, which predicts the number of NHL games played. Both models are presented below separately for forwards and defensemen.

Forwards

As displayed in Table 7, seven independent variables were significant predictors in the zero-inflation model.

Table 7. Zero-inflation model in the forwards' sample

Variable	Estimated Coefficient	OR	Z-Value	*p*
Constant	-7.09	<0.01	-0.82	0.41
CESCIN-adjusted CSB ranking	<0.01	1.00	2.25	0.03
Height	0.02	1.02	0.25	0.80
Weight	0.00	1.00	-0.28	0.78
Age (months)	0.03	1.03	1.10	0.27
GP	0.03	1.03	4.04	<0.01
NHLe PPG	-10.47	0.00	-5.54	<0.01
PIMs/GP	0.08	1.09	0.39	0.70
Plus/minus (+/-)	-0.02	0.98	-2.53	0.01
Shot blocking ability	-0.45	0.64	-0.93	0.35
Defensive awareness	-0.19	0.83	-0.52	0.60
Puck protection ability	-0.51	0.60	-1.56	0.12
Board battles	-0.77	0.46	-2.45	0.01
Work ethic & leadership	-0.22	0.80	-0.74	0.46
Willingness to fight	0.64	1.89	1.55	0.12
Soft hands	0.01	1.01	0.05	0.96
Shooting ability	0.12	1.12	0.42	0.68
Passing & playmaking ability	-0.02	0.98	-0.07	0.94
Lack of physical strength	-0.46	0.63	-1.53	0.13
Inconsistency in effort & performance	-0.32	0.73	-1.00	0.32
Hockey sense	-0.91	0.41	-2.58	0.01
Backchecking ability	-1.00	0.37	-2.46	0.01

CESCIN = Central Scouting Integrator; CSB = Central Scouting Bureau; GP = Games Played; NHLe PPG = National Hockey League Equivalency Points Per Game; OR = Odds Ratio; PIMs = Penalty Minutes

In particular, draftees with higher NHLe PPG and plus/minus were significantly less likely to play zero games in the NHL. Similarly, those who battled for puck possession along the boards, had high hockey sense, and good backchecking ability were also less likely to belong in the certain zero group by factors of 0.46, 0.41, and 0.37, respectively. On the other hand, forwards that were ranked higher by CSB and played more games in their final pre-draft season were significantly more likely to play zero NHL games during the first five years post draft.

In terms of the second partial model, only two variables were significant predictors of NHL GP (Table 8), NHLe PPG and good passing and playmaking ability.

Table 8. Count model in the forwards' sample

Variable	Estimated Coefficient	IRR	Z-Value	*p*
Constant	3.15	23.37	0.57	0.57
CESCIN-adjusted CSB ranking	<0.01	1.00	-0.19	0.85
Height	0.08	1.08	1.23	0.22
Weight	<0.01	0.99	-0.30	0.77
Age (months)	-0.02	0.98	-1.08	0.28
GP	-0.01	0.99	-1.52	0.13
NHLe PPG	2.93	18.68	3.41	0.001
PIMs/GP	-0.10	0.91	-0.70	0.49
Plus/minus (+/-)	0.01	1.01	1.08	0.28
Shot blocking ability	0.23	1.25	0.77	0.44
Defensive awareness	-0.10	0.91	-0.44	0.66
Puck protection ability	0.04	1.04	0.21	0.83
Board battles	0.14	1.15	0.77	0.44
Work ethic & leadership	-0.05	0.95	-0.28	0.78
Willingness to fight	-0.21	0.81	-0.71	0.48
Soft hands	0.05	1.05	0.30	0.77
Shooting ability	-0.09	0.92	-0.48	0.63
Passing & playmaking ability	0.49	1.63	2.39	0.02
Lack of physical strength	-0.09	0.91	-0.49	0.63
Inconsistency in effort & performance	-0.14	0.87	-0.72	0.47
Hockey sense	-0.03	0.97	-0.14	0.89
Backchecking ability	0.20	1.22	0.93	0.35
Log (theta)	-0.29	0.75	-2.74	0.01

CESCIN = Central Scouting Integrator; CSB = Central Scouting Bureau; GP = Games Played; IRR = Incidence Risk Ratio; NHLe PPG = National Hockey League Equivalency Points Per Game; PIMs = Penalty Minutes

As displayed in Table 8 above, for a one unit increase in NHLe PPG, a prospect would increase his rate of NHL GP by a factor of 18.68. Similarly, a prospect who possessed good playmaking ability increased his rate of NHL GP by 1.63 times compared to a prospect who did not possess that ability.

Interestingly, none of the other independent variables were significant differentiators between draftees in terms of future success. Moreover, all other variables had small effect sizes as indicated by their IRR and estimated coefficients.

Defensemen

As shown in Table 9, only four independent variables were significant predictors in the zero-inflated model. In order from largest to smallest effect sizes these were: NHLe PPG, height, passing and playmaking ability, and plus/minus. All variables had negative estimated coefficients, meaning defensemen with higher values on these four variables were less likely to belong in the certain zero group. For instance, for each inch increase in height, a defensemen's odds of playing zero games decreased by a factor of 0.65. Similarly, defensemen who had good passing and playmaking ability were less likely to belong in the zero group by a factor of 0.31.

Although this effect was not statistically significant, defensemen who were described as lacking physical strength were more likely to not play in the NHL by a factor of 1.64, which is a considerable effect size. As for other independent variables, not only were they non-statistically significant, their OR values were markedly close to 1.00 indicating small effects.

Table 9. Zero-inflated model in the defensemen's sample

Variable	Estimated Coefficient	OR	Z-Value	*p*
Constant	31.60	<0.01	2.66	0.01
CESCIN-adjusted CSB ranking	0.00	1.00	1.59	0.11
Height	-0.44	0.65	-3.39	<0.01
Weight	0.02	1.02	1.24	0.22
Age (months)	0.00	0.99	-0.08	0.93
GP	-0.01	0.99	-0.59	0.55
NHLe PPG	-13.37	<0.01	-3.73	<0.01
PIMs/GP	-0.23	0.80	-0.76	0.45
Plus/minus (+/-)	-0.03	0.97	-2.18	0.03
Shot blocking ability	-0.53	0.59	-0.80	0.42
Defensive awareness	-0.17	0.84	-0.46	0.65
Puck protection ability	0.00	1.00	0.01	0.99
Board battles	-0.19	0.83	-0.43	0.67
Work ethic & leadership	-0.58	0.56	-1.14	0.26
Willingness to fight	-0.20	0.82	-0.33	0.74
Soft hands	-0.40	0.67	-0.79	0.43
Shooting ability	0.26	1.30	0.72	0.47
Passing & playmaking ability	-1.16	0.31	-2.49	0.01
Lack of physical strength	0.50	1.64	1.15	0.25
Inconsistency in effort & performance	0.08	1.08	0.15	0.88
Hockey sense	-0.15	0.87	-0.23	0.82
Backchecking ability	0.02	1.02	0.02	0.98

CESCIN = Central Scouting Integrator; CSB = Central Scouting Bureau; GP = Games Played; NHLe PPG = National Hockey League Equivalency Points Per Game; OR = Odds Ratio; PIMs = Penalty Minutes

In terms of the count model, three independent variables were significant predictors of NHL games played: GP, NHLe PPG, and work ethic and leadership. GP was the lone negative predictor, wherein more games played in junior led to fewer NHL games played. On the other hand, NHLe PPG and work ethic and leadership were positive predictors, with higher values on these two variables related to greater success in the NHL.

Backchecking ability, although not statistically significant, had a substantial effect on NHL GP. In fact, defensemen who retreat back to the defensive zone efficiently have a higher rate of games played by a factor of 2.33. As for other variables, they presented non-significant results with low effect sizes.

Table 10. Count model in the defensemen's sample

Variable	Estimated Coefficient	Incidence Risk Ratio	Z-Value	*p*
Constant	1.36	3.88	0.22	0.83
CESCIN-adjusted CSB ranking	<0.01	1.00	-0.74	0.46
Height	0.03	1.03	0.39	0.69
Weight	<0.01	1.00	0.04	0.97
Age (months)	0.01	1.01	0.31	0.76
GP	-0.02	0.98	-2.36	0.02
NHLe PPG	6.03	413.90	3.54	<0.01
PIMs/GP	-0.31	0.73	-1.49	0.14
Plus/minus (+/-)	0.003	1.00	0.32	0.75
Shot blocking ability	-0.27	0.76	-0.81	0.42
Defensive awareness	-0.03	0.97	-0.13	0.90
Puck protection ability	0.15	1.16	0.55	0.58
Board battles	0.17	1.18	0.58	0.56
Work ethic & leadership	0.61	1.82	2.07	0.04
Willingness to fight	-0.05	0.95	-0.16	0.87
Soft hands	0.17	1.19	0.50	0.62
Shooting ability	0.37	1.45	1.44	0.15
Passing & playmaking ability	-0.63	0.53	-1.79	0.07
Lack of physical strength	0.23	1.26	0.89	0.38
Inconsistency in effort & performance	-0.37	0.69	-1.01	0.32
Hockey sense	-0.14	0.87	-0.38	0.71
Backchecking ability	0.85	2.33	1.15	0.25
Log (theta)	-0.18	0.83	-1.23	0.22

CESCIN = Central Scouting Integrator; CSB = Central Scouting Bureau; GP = Games Played; IRR = Incidence Risk Ratio; NHLe PPG = National Hockey League Equivalency Points Per Game; PIMs = Penalty Minutes

Discussion

The purpose of this study was to identify inefficiencies in the NHL draft by determining the predictors of draft order and examining how such predictors fare in projecting future NHL performance. To do so, we relied on (a) pre-draft performance metrics, (b) anthropometric and demographic measures (height, weight, and age), and (c) attributes extracted from text-mined scouting reports. The following section discusses findings from each of those three data categories, highlights the overlap between predictors of selection and success, and offers solutions to certain observed inefficiencies.

Standard performance metrics

Findings from the sample of forwards showed that players rated lower by CSB rankings (i.e., had higher ranking number) and more GP in their final pre-draft season were selected later. Such players were also found to be more likely to play zero NHL games in the future. Similarly, NHL teams selected forwards with higher NHLe PPG earlier in the draft, and those players were subsequently more likely to achieve success in the NHL. This suggests that teams' utilization of CSB ranking, GP, and NHLe PPG was accurate when selecting forwards.

However, inefficiencies were found in other areas. For instance, players who took more penalties per game (PIMs/GP) were taken significantly earlier in the draft, yet they did not have any more success in the NHL than their peers. In fact, they were less likely to – although not significantly – play in the NHL. As previously mentioned, players who fight more accumulate more penalties; therefore, this finding likely reflects teams' overvaluation of "toughness" and willingness to engage in fights. Despite teams' preference for tough forwards, recent rule changes such as 'the instigator penalty', along with increased understanding of the consequences of repeated head trauma, have resulted in a marked decrease in the occurrence of fights, making the role of fighters on NHL teams almost obsolete (Depken et al., 2020; Smith et al., 2019). In addition, players who accumulate penalties due to reasons other than fighting (i.e., minor and major penalties) often put their teams in disadvantageous shorthanded situations due to their lack of on-ice discipline, which may also explain why such prospects do not end up making the NHL.

Another observed inefficiency was that forwards' pre-draft plus/minus was undervalued, as it did not predict selection order despite those with higher plus/minus turning into more successful NHL players. It is important to mention that plus/minus, as a metric, has notable limitations as it can be highly confounded by the quality of a player's teammates. For instance, even if a player performs well offensively and contributes to scoring goals, his plus/minus will still suffer if the team's defensive structure is weak and allows too many goals (Nandakumar & Jensen, 2019). Despite this limitation, this metric may have good evaluative utility that teams overlooked at the draft, as it can indicate which forwards are defensively savvy. This is because in power play situations, a player does not receive a +1 if his team scores with a man-advantage, but would receive a -1 if his team concedes a shorthanded goal. Likewise on the penalty kill, a player does not receive a -1 if his team concedes a goal, but would receive a +1 if his team scores a shorthanded goal. Hradek (2002) described this metric of putting offensive minded players in minus-only positions, and defensive minded players in plus-only positions. As such, when interpreted with caution, this metric may be able to distinguish good defensive forwards from others, especially in junior leagues where more sophisticated analytics are not available.

As for defensemen, teams selected those with higher NHLe PPG earlier in the draft, which was found to be a good strategy given that such players went on to play more games in the NHL. Moreover, teams drafted defensemen with better (higher) plus/minus earlier. While such defensemen were less likely to play zero games, suggesting accurate decision-making, they were not more likely to accumulate more games once they are in the NHL. This suggests plus/minus has the predictive ability to differentiate between defensemen who debut in the NHL and ones who do not, but not beyond that point.

In terms of inefficiencies, teams overvalued CSB rankings in the draft, as they selected defensemen in accordance with how CSB ranked them, yet these rankings were not predictive of future performance in any capacity. The contrast between CSB's predictive ability for forwards and defensemen is noteworthy, and may be explained by two factors. First, a major part of CSB's ranking of defensemen involves evaluating and rating their defensive capabilities, which is considered among the biggest challenges in hockey (Nandakumar & Jensen, 2019). Unlike offensive ability in forwards, which is easier to measure because it involves quantifying on-ice events that *did occur* (goals, shots, scoring chances, etc.), evaluating defensive performance involves rating a defenseman's ability to prevent on-ice events from *occurring in the first place* (i.e., preventing cross ice passes, preventing transitions, etc.), which makes quantifying this attribute more challenging. This is particularly difficult in junior leagues where data is limited. Second, similar to NHL teams' own internal evaluation, CSB's ranking of defensemen involves projecting how they will perform years later into the future, which is a more challenging task than that of forwards. This is because defensemen typically require more time in the minor leagues to develop and become accustomed to the speed and structure of professional hockey (Chang, 2011). This, in turn, increases the duration between the point at which the forecast is made (draft) and the point when the outcome is determined, thereby decreasing the likelihood of accurate projection (Farah & Baker, 2020; Smith & Sincich, 1991; Swets, 1988).

Anthropometric and demographic measures

In the forwards' sample, players' weight was not predictive of draft order or future performance, suggesting teams rightfully dismissed this variable in their evaluation. This is likely due to teams recognizing that body weight is rather malleable and can be adjusted with training and nutrition programs. It may also be due to teams placing more value on sophisticated physiological measures obtained through combine testing, such as power output, aerobic and anaerobic fitness, and agility (Burr et al., 2008; Tarter et al., 2009; Vescovi et al., 2006). As for height, however, teams drafted taller forwards significantly earlier than shorter ones. In fact, holding all other variables constant, a one-inch increase in a forward's height resulted in him being selected five picks earlier. Yet, height was not found to be predictive of future performance in the NHL. Although taller forwards did not end up performing *worse*, this finding still highlights an inefficiency in drafting, as it suggests teams "waste" valuable draft picks based on a non-predictive attribute instead of using them to draft players with attributes of actual predictive ability of NHL performance.

Similarly, age was a significant predictor of draft order, wherein older forwards were selected later than younger ones but did not go on to play more NHL games. While our analysis suggests this is a draft inefficiency, there is previous contradictory evidence showing that age is, in fact, a significant predictor of forwards' NHL games played (Hohl, 2015). This incongruence between the two findings may be attributed to difference in variables used in each model, as Hohl's (2015) analysis included height, age, and PPG, while our model included these variables and 17 additional ones. Moreover, Hohl's analysis used a linear regression model, while the current study used ZINB. It should be noted, however, that Age-Adjusted Scoring (AAS), which accounts for a prospect's scoring rate relative to his age, has been shown to be a good predictor of future performance by other models (Hohl, 2016; Vollman et al., 2016). Therefore, while the effect of age – on its own – is inconclusive, teams should still take this variable into consideration within the context of point scoring.

As for findings pertaining to defensemen, analyses showed that weight and age were non-significant predictors of draft order or future performance, and that effect sizes associated with each were rather small. Height, on the other hand, was a significant predictor of draft order. Furthermore, taller defensemen were significantly less likely to play zero NHL games. This suggests that while NHL teams value height in both forwards and defensemen, this valuation is only accurate in the latter group. This finding supports prior research by Weissbock (2015), who found that defensemen's height was a significant predictor of reaching the milestone of 200 NHL games.

Although it is not clear why height is a determinant of success for defensemen but not forwards, one may be able to deduce some plausible reasons based on the differences in demands between the two positions. First, defensemen are more likely to be on the receiving end of hits from forecheckers in the defensive zone (Kearns, 2015). Second, defensemen are responsible for separating the puck from its carrier, and "clearing" the area surrounding their own net from the opposition's forwards, by exerting considerable physical force. Therefore, given that defensemen are tasked with applying a more "physical" style of play, such demands may favor bigger (taller) players, who might perform these tasks more efficiently than their peers who are smaller in stature.

Attributes extracted from text-mined scouting reports

Results pertaining to text-mined scouting reports highlighted a variety of efficient and inefficient practices. In the forward group, those who were described as having good passing and playmaking ability were selected earlier in the draft, which reflects sound decision-making as such players went on to accumulate more games in the NHL. From a hockey dynamics perspective, this finding is intuitive as good passers would be better at distributing the puck through the neutral zone for successful entries, creating high-danger scoring chances in the offensive zone, and maintaining possession for their team by making accurate passes and not turning the puck over. From a perceptual cognitive standpoint, however, these results may be attributed to a skill known as "scanning" (Jordet et al., 2013).

In skill acquisition literature, scanning is defined as the frequency – and duration – of eye movements by which a player gathers information on teammates/opponents prior to making a decision with the object (i.e., ball, puck, etc.) (Aksum et al., 2021; Jordet et al., 2020). In the current study, two of the most important keywords/phrases in the *good passing and playmaking* attribute – as measured by factor loading – were "vision" and "seeing the ice" (Table 2), both of which can be considered proxies for players' scanning ability. Thus, the observed relationship between *good passing and playmaking* and NHL success are in line with past research in other sports. For instance, Aksum et al. (2021) found a positive relationship between scanning frequency and passing accuracy in European soccer players. The authors attributed these findings to players with higher scanning frequency being able to extract more information regarding their surrounding environment, thereby allowing them to locate open passing lanes more accurately. Likewise, Phatak and Gruber (2019) found a significant positive relationship between scan rate and passing accuracy in elite soccer players, and a significant negative relationship between transition scan rate[8] and turnovers. Lastly, Jordet et al. (2013) found that English Premier League (EPL) players who received individual awards had higher scan rates than those who did not. Findings from such studies, combined with ours, suggest that in addition to evaluating players' "vision" and ability to "see the ice" using current practices, NHL teams may benefit from empirically measuring scanning ability – using similar video techniques used in such studies – to further supplement their evaluation. Moreover, teams may also benefit from developing this skill in their drafted prospects to increase their chances of NHL success.

In terms of inefficiencies, our analyses showed that forwards identified as lacking physical strength were selected significantly earlier than those who were not. Yet, these players did not end up having more NHL success by any measure. Albeit an inaccurate decision, this

[8] The term "transition scan", as defined by Phatak and Gruber (2019), refers to scanning performed by the player who is about to receive the ball after it had left the foot of the passer (i.e., while the ball is in transition).

judgement process can be rationalized from the perspective of talent selectors. Since players are drafted in their teenage years, it is expected that many of them are not fully developed from a physiological standpoint. Therefore, lacking physical strength can be viewed as simply a virtue of age rather than a weakness. However, the fact that such players were drafted *earlier* may reflect an element of "untapped potential", which is defined by Moxley and Towne (2015) as the notion that "two equally skilled individuals could be different distances from the limits of their talents" (p.2). In accordance with this line of thinking, if two junior players have similar performance outputs but one lacks physical strength while the other does not, NHL teams may be inclined to draft the former rather than the latter, as he might have more "untapped potential" (i.e., higher ceiling) which he could reach with exposure to professional-level strength and conditioning training and nutrition. In fact, in statistical terms, our results point to this line of thinking being prevalent, since the regression model holds all other variables constant (i.e., assumes performance outputs are equal). Despite this selection strategy being appropriate, findings from this analysis suggest players who lack physical strength do not go on to achieve more success once they are in the NHL.

Other observed inefficiencies in the forward group include the findings that players who engage in puck battles, have good backchecking ability, and have good hockey sense are significantly less likely to play zero NHL games, yet these attributes did not impact draft order. The first two attributes (puck battles and backchecking) are defensive qualities surrounding players' ability to force pressure on opponents in order to regain possession of the puck. Therefore, it is logical that players who help their team maintain possession, and regain it once its lost, become more successful in the future. As for hockey sense, while this attribute does not have an official operational definition, it is a widely used term that describes various facets of a player's intelligence, particularly, a player's ability to anticipate events and react to them quickly, and to make appropriate on-ice decisions. The finding that players who possess such an attribute were not drafted earlier was rather surprising, especially given that NHL style of play demands quick, and accurate, decision making as opponents are able to prevent time and space much more effectively than they are at the junior or collegiate level. While there is no research, to our knowledge, on hockey-specific decision making and intelligence, studies on other sporting contexts support the importance of this attribute on athletic achievement. In fact, compared to their non-elite counterparts, elite athletes display significantly quicker, and more accurate, anticipation and decision-making skills in sports such as badminton, basketball, and Australian football (Camponogara et al., 2017; Lorains et al., 2013; Schorer et al., 2013; Wright et al., 2011). Indeed, quantifying and tracking decision-making and anticipation outside of experimental settings is no easy task for scouts; however, the finding that players labeled with good hockey sense end up performing better than their peers is an indication that scouts – to an extent – are able to identify this quality in players and assess it. What our results suggest, however, is that this variable should have more weight in selection decisions than other non-predictive variables.

As for the sample of defensemen, our analysis showed that although a few text-mined attributes predicted NHL success well, none were significant predictors of draft order. The first of these attributes is *passing and playmaking ability*, wherein players who possess this quality were significantly less likely to play zero NHL games. The importance of this attribute on hockey performance was discussed above in the forwards' section; both from a hockey dynamics and perceptual cognitive standpoints (Jordet et al., 2020). However, in addition to these factors, there is an added position-specific element that should be mentioned, that is the importance of playmaking ability on “breakouts” for defensemen. Breakouts is a term used to describe the transition of the puck out of the defensive zone and into the neutral zone, which is an important play to execute as it reduces the time opponents spend in one’s defensive end and, in turn, leads to fewer scoring chances against. Since the execution of this play most often falls primarily on defensemen, the impact of *passing and playmaking ability* on making the NHL may also be explained by this component.

The second variable shown to impact the odds of playing zero NHL games – albeit non-significantly, but with a large effect size – was *lack of physical strength*. Contrary to forwards, whose odds of making the NHL were not affected by this attribute, defensemen lacking physical strength were more likely to never play a game in the NHL. This highlights the position-specific differences in demands between forwards and defensemen, as the latter may require exerting more physical force in tasks such as clearing the net, separating the opposition from the puck upon entry using contact, among others. This also supports prior research on physiological differences between the two positions, which showed that defensemen are not only taller and heavier, but are also stronger on non-body weight dependent tests (Burr et al., 2008).

The third influential variable on defensemen’s NHL success was *work ethic and leadership*, where players described as having this quality played significantly more NHL games than those who did not. Interestingly, this attribute was only influential on career success in defensemen but not forwards. Indeed, this is not to suggest work ethic is not important to forwards’ career progression; however, a possible explanation to this observation is that there are twice as many NHL roster spots for forwards as there are for defensemen, making competition for the latter to earn an NHL spot much closer. As a result, it is plausible that one of the very few separating factors between those who earn such limited spots, and those who do not, is their work ethic and dedication to improvement. Lastly, ZINB analyses showed defensemen with good *backchecking ability* played significantly more games in the NHL. This finding was also observed in the forwards' group, and may be explained by the same underlying mechanisms discussed in that section.

Implications

Research implications

Although text-mining NHL scouting reports has been done before (Seppa et al., 2017), the use of extracted attributes to uncover draft inefficiencies is a novel approach, and with that comes the need for replication. Results presented in this study have uncovered a myriad of over-and-under valued attributes in selection; however, similar research using different reports, or different draft classes, is needed in order to generalize these findings. In addition, future research may benefit from integrating different variables into similar prediction models, such as combine data (i.e., physical test scores), or pre-draft advanced performance metrics (analytics) which have become more available for the public in recent years.

Practical implications

The current research presents a variety of under-and-over valued attributes in the draft. However, as mentioned above, NHL talent identification personnel should approach our findings and apply them with caution as replication is needed to confirm these inefficiencies. For instance, although our results show that *hockey sense* is undervalued at the draft, we recommend that – instead of simply drafting more players with this attribute – that NHL decision makers evaluate whether this attribute is, in fact, valued improperly in their selection criteria and consider why that may be the case.

Limitations

The current study offers a novel perspective on talent identification in the NHL; however, there are some notable limitations to its design. First, although scouting reports used in the analysis were collected from a reputable scouting agency, they were not obtained from NHL scouting departments, who ultimately have substantial influence on the actual selection process. As mentioned, the proprietary nature of such data makes it practically inaccessible to researchers. However, it is important to highlight that although this is indeed a limitation of the data, it is also a strength. To elaborate, prospect evaluations from team-employed scouts may be heavily influenced by the team's "identity" and style of play. As a result, such evaluations often focus on how the observed prospect may fit within a specific organizational system, as opposed to evaluating his overall ability from a neutral standpoint. For example, a player who is small in stature but is fast and highly-skilled may be praised by a scout employed by a team that is built on speed and skill (e.g., Toronto Maple Leafs), but condemned by a scout whose team is built on size, physicality and toughness (e.g. late 2000s Boston Bruins). Contrarily, reports from independent agencies – such as the ones utilized in this research – may offer a more neutral perspective on players without focus on specific systems.

Another notable limitation is that part 1 of our analysis (i.e., the linear regression model) only explained 37.5% and 40.6% of the variance in draft order for forwards and defensemen, respectively. This leaves a substantial amount of variance unexplained by the model, and may be explained by several factors: (a) intangible qualities unaccounted for, or uncaptured, in our scouting reports; (b) pre-draft advanced analytics (e.g., possession metrics, expected goals, etc.) that were not captured in this study, as this data is rather scarce in junior leagues for draft classes of 2007-2014, and is mostly proprietary to NHL organizations who employ independent agencies to track them; and (c) NHL combine data including various fitness testing scores (e.g., lower and upper body strength, aerobic and anaerobic fitness, etc.), which were also not unaccounted for in this research due to their proprietary nature.

Conclusion

Making successful draft selections is of critical importance to the long-term success of NHL organizations, and can be the difference maker between winning championships and years of mediocrity. Yet, there remains a paucity of research evaluating draft inefficiencies. This study addresses some of those gaps by examining the over-and-under valued variables involved in NHL selection processes. Results showed a variety of pre-draft performance metrics, anthropometric measures, and text-mined scouting attributes that are commonly given too much, or too little, value at the draft. Both research and practical implications were then discussed, encouraging researchers to replicate findings presented in this research, and providing practitioners with evidence-based strategies to enhance their scouting operations.

Chapter Four

Eliminating buyer's remorse: An examination of the sunk cost fallacy in the National Hockey League draft

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Abstract

The sunk cost effect describes the tendency to escalate one's commitment towards a certain endeavor, despite diminishing returns, as a consequence of irreversible resource expenditure that has already been made.1 This effect has been observed in a number of professional sports leagues, wherein teams escalate their commitment towards players selected early in the draft, regardless of performance outcomes, due to large financial commitments invested in them. This effect, however, has yet to be explored in the National Hockey League (NHL). The purpose of this study was to test for sunk cost effects in the NHL, by examining the relationship between draft order and playing time, while controlling for a myriad of confounding variables. Findings from our analyses provide support for the existence of this effect in the NHL, as first round draftees were given significantly more playing time than their peers selected in the second round, regardless of injury, player relocation, penalties or on-ice performance outcomes. We offer some plausible underlying mechanisms driving this effect. Furthermore, we suggest the observed effects have valuable implications for NHL talent development, given the importance of playing time on various aspects of expertise attainment.

Keywords: National Hockey League, sunk cost effect, escalation of commitment

Introduction

The fields of psychology and behavioral economics have identified a plethora of cognitive biases that drive irrational decision-making (Ariely, 2008). In certain cases, decisions motivated by biases can be detrimental to the efficiency and productivity of organizations. A prominent example of such is the "sunk cost fallacy" (also known as escalation of commitment), referring to the tendency to continuously and wastefully commit time, money and effort towards a fruitless endeavour – despite the costs far outweighing the rewards – simply because a "sunk cost" had already been expended (Staw, 1976). Or, in the words of Garland (1990): "throwing good money after bad".

North American professional sports organizations have been shown to exhibit this fallacy as a consequence of the "entry draft", a talent identification and selection system wherein teams take turns selecting from a talent pool of young amateur athletes for the purpose of signing them to professional contracts.[9] In some sports, athletes receive varying salaries and bonuses depending on the position in which they were drafted - the earlier the draft pick, the higher the monetary reward. This has been shown to drive teams to provide their highly drafted athletes with more playing time than their counterparts drafted in later rounds, *regardless of performance outcomes*, as a consequence of the large irreversible monetary investments that have been made. Evidence of sunk cost effects in sports were first reported by Staw and Hoang (1995), who showed that National Basketball Association (NBA) players taken early in the draft played more minutes, had longer careers and were less likely to be traded than their peers selected later, even after controlling for their on-court performance. Likewise, Camerer and Weber (1999) found

[9] While the draft consists of mostly amateur players, there are some exceptions in basketball, baseball, and hockey where professional international players are considered draft-eligible.

supporting evidence for such effects in the first three years after being drafted. Interestingly, however, sunk cost effects seem to have diminished after the introduction of the 1995 NBA Collective Bargaining Agreement (CBA) (Leeds et al., 2015). Under this current agreement, rookie contracts are no longer negotiated between teams and first round draftees; instead, they are pre-determined by the league itself. This may have alleviated some of the responsibility and commitment that general managers would have otherwise experienced had they decided the size of the monetary value themselves, and may explain such findings.

Unlike the NBA, however, escalation of commitment seems to be persistent in the National Football League (NFL). Keefer (2017) found that players drafted late in the first round receive wages that are 30% higher than second round draftees. Consequently, first round draftees start significantly more games despite not being any more productive in terms of performance, as measured by the Defense-Adjusted Value Over Average (DVOA) metric. In fact, a 10% increase in salary cap value resulted in 2.7 more games started. Not only has this effect been observed following the NFL draft, but in free agency as well, as players who sign more lucrative contracts as free agents receive significantly more playing time simply as a virtue of their earnings rather than performance (Keefer, 2015).

While the literature has uncovered a great deal about this fallacy in other sport leagues, the National Hockey League (NHL) remains unexamined. This is likely due to the fact that the salaries of NHL draftees do not vary based on draft order. Instead, Entry Level Contracts (ELC) are standardized with a maximum annual salary of $925,000 plus a maximum of 10% signing bonus. All other bonuses that a draftee receives under his ELC are "performance bonuses" and are only paid *after* the player has achieved certain objectives in the NHL (Collective Bargaining Agreement between National Hockey League and National Hockey League Players' Association, 2013). This means that, contrary to other sports, there are no differences in irreversible *monetary* sunk costs that are inherent within the draft structure. However, considering each team is allocated only one draft pick per round, merely using a draft pick to select an athlete constitutes an irreversible resource expenditure and an opportunity foregone to select another athlete that could develop into a better player (Staw & Hoang, 1995). This is particularly relevant in the first round, during which draft picks are considered highly valuable assets to NHL organizations given that first round draftees, on average, have superior careers than players drafted later (Koz et al., 2012; Schuckers, 2011; Shoniker, 2015). However, whether or not such non-monetary sunk costs lead to escalation of commitment remains to be investigated. Furthermore, the importance of studying this effect extends beyond merely addressing a research gap, as disproportionate allocation of playing time – by virtue of escalation of commitment – may have implications for the development of draftees, given the influence of playing time on expertise attainment in sport (Baker et al., 2003; Baker & Young, 2014).

As such, the purpose of this study is to test for sunk cost effects in the NHL by examining the relationship between draft round and playing time, while controlling for on-ice performance and other confounding variables. Similar to prior research in draft settings (Keefer, 2017; Staw & Hoang, 1995), we restrict our analysis to the first two rounds of the draft in order to focus on the highest resource expenditure. We hypothesized that the sunk cost effect exists in the NHL, given the high value of a first round pick as an organizational resource.

Methods

Sample

The sample consisted of all forwards drafted in the first two rounds from 2007-2014, who played at least one NHL game in the first five years after being selected (N = 219). This particular time period was chosen as the majority of "advanced" NHL performance metric, such as the ones used in this study, have only become publically available since 2007. Moreover, 2014 was set as a cut-off year to allow for data collection within the first five years post draft (i.e., the end of the 2018-2019 regular season).[10]

Variables

The *dependent variable* used in this study was players' 5-on-5 Time on Ice per Game (TOI/G), which – as in previous sunk cost literature in sports – represents the size of the escalation of commitment NHL organizations exhibit. We excluded playing time on power plays and penalty kills as only a select few receive such assignments on each team, making it unfeasible to control for performance across all players. The main *independent variable* was draft round, which represents the size of the sunk cost expended. Draft round was chosen for this analysis in lieu of the specific pick number as our primary purpose is to measure the difference in playing time from one round to the next, as opposed to an intra-round comparison. In other words, to investigate how NHL teams' perceived value of a first round pick influences sunk cost effects, as opposed to how they utilize, for instance, pick #18 compared to pick to pick #19. Moreover, it was important for our independent variable to capture the "cost" of an organizational resource, and the round in which a player was selected represents a better – and more natural – categorization of such cost compared to the crude selection number.

As for *confounding variables*, considering the absence of empirical evidence highlighting the specific determinants of ice time in the NHL, we controlled for a variety of factors that could

[10] It is important to mention that the sample size of defensemen who fit our selection criteria was almost half of that of forwards, which yielded exceedingly weak statistical power that was deficient for this study design. As a result, defensemen were excluded from our analysis.

influence playing time (see Table 1) based on the following theoretical grounds: (a) *injury* - being injured not only results in missing games – and therefore missing playing time – but may result in decreased ice time after returning to play as part of rehabilitation to manage physical load. (b) *Penalties* – penalties in ice hockey result in time spent in the penalty box (duration varies depending on the penalty), which results in less time spent on the ice. In addition, taking a penalty puts one's team at a disadvantage as they would be short-handed for the duration of the penalty. Subsequently, taking many penalties may result in a coach limiting a player's ice time as punishment for his lack of on-ice discipline. (c) *Relocation* (i.e., traded or claimed off of waivers) - as indicated by Staw and Hoang (1995), a player may see an increase in playing time if he moves from a team that does not need his services to one that does, or a decrease in playing time if his trade/placement on waivers was due to insufficient on-ice production. (d) *Relative Expected Goals For* (*RelxGF/60) and Relative Shooting Percentage (RelSh%)* - both of which provide indicative measures of offensive outcomes, which – if sufficient enough – would theoretically be rewarded with more ice time as they would likely lead to more goal scoring. In fact, "expected goals" (represented in RelxGF/60) has been shown to be highly predictive of future goal scoring (Nandakumar & Jensen, 2019) (e) *Relative Expected Goals Against (RelxGA/60) and Relative Save Percentage (RelSv%)* - both metrics provide the same measurements as RelxGF/60 and RelSh% but against one's own team. Therefore, they indicate defensive outcomes that may decrease a player's ice time if his performance leads to more goals conceded. Lastly, (f) *Individual Giveaways (iGVA/60) and Individual Takeaways (iTKA/60)* - giving away the puck is viewed as an error which, anecdotally, often results in the player being "benched" as a form of discipline; conversely, taking the puck away creates the opposite effect for one's team and may therefore be rewarded.

Table 1. Confounding variables controlled for in the regression analysis

Variable	Definition	Description
Penalties (iPENT/60)	Individual penalties taken by the player per 60 minutes of ice time	Higher value indicates more penalties taken
Injury	A dummy variable indicating whether a player had suffered any type of disclosed injury	1 indicates no injury, 2 indicates injury
Relocation	A dummy variable indicating whether a player had been relocated by his original team (i.e., traded or placed on waivers then claimed by another team)	1 indicates no relation, 2 indicates relocation
Relative Expected Goals For (RelxGF/60)	Quality of scoring chances for the team when the player is on the ice compared to when he is off the ice	Higher value indicates better performance
Relative Expected Goals Against (RelxGA/60)	Quality of scoring chances against the team when the player is on the ice compared to when he is off the ice	Lower value indicates better performance
Relative Shooting Percentage (RelSh%)	The percentage of shots resulting in goals for the team when the player is on the ice compared to when he is off the ice	Higher value indicates better performance
Relative Save Percentage (RelSv%)	The percentage of shots resulting in goals against the team when the player is on the ice compared to when he is off the ice	Higher value indicates better performance
Individual Giveaways (iGVA/60)	The number of times a player loses possession of the puck to the opposition	Lower value indicates better performance
Individual Takeaways (iTKA/60)	The number of times a player gains possession of the puck from the opposition	Higher value indicates better performance

All seven performance metrics listed above were measured per 60 minutes of ice time, as that provides a better indicator of a player's production rate compared to raw totals. Moreover, four of the metrics were measured on a relative-to-team basis, denoted by "Rel". Relative metrics measure the individual impact that a player has on his team by subtracting the team's performance when the player is off the ice from the team's performance when he is on the ice. Subsequently, these metrics account for the quality of the team a player is on, which may also play a factor in how much ice time he receives. For instance, players selected into poorly performing teams may have less difficulty finding playing time compared to draftees who play on rosters of high-quality (Staw & Hoang, 1995).

Lastly, a notable omission from the regression analysis was points scored (i.e., goals plus assists). This was due to the fact that including points in the analysis introduced substantial multicollinearity into the model, while only explaining an additional 0.1% of the variance in TOI/G. In lieu of points, RelxGF/60 offers a better predictor of TOI/G, and provides a more comprehensive assessment of a player's individual impact on his team's offensive success.

Analysis

A two-step hierarchical multiple linear regression analysis was conducted using SPSS. All nine confounding variables listed in Table 1 were entered in the first step as control variables, prior to entering "draft round" in the second step as the main independent variable of interest. Standardized and unstandardized beta coefficients, t-statistics, 95% confidence intervals, and semi-partial correlations were calculated and reported.

In regard to model diagnostics, the assumptions of no multicollinearity [mean Variance Inflation Factor (VIF) = 1.34, VIF range = 1.01 – 2.14], and independent errors [Durbin-Watson (D-W) statistic = 1.80) were both tested and substantiated successfully. In addition, normality, homoscedasticity and linearity assumptions were tested and verified using frequency histogram, standardized predicted values versus standardized residual plot, and partial regression plots, respectively. As for statistical power, it was not possible to determine the sample size needed *a priori*, given that no previous studies have examined the size of this effect in NHL data. Instead, we conducted retrospective post-hoc power analysis, which revealed that the sample size, combined with the observed effect sizes, yielded a power of 0.99.

Lastly, standardized residuals identified one player in the data as an outlier. However, given that no measurement errors were identified, and that the player had accumulated 10 games in the NHL (i.e., his metrics were not inflated due to an exceedingly small number of games played), the outlying case was not removed from the analysis.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Results

Table 2 outlines the descriptive statistics (mean and standard deviation) of the independent and dependent variables utilized in the analysis.

Table 2. Descriptive statistics of the independent and dependent variables

Variable	Mean	Standard deviation	N
TOI/G	11.28	1.88	219
iPENT/60	0.80	0.87	219
Injury	1.74	0.44	219
Relocation	1.25	0.43	219
RelxGF/60	-0.07	0.39	219
RelxGA/60	-0.07	0.31	219
RelSh%	-0.65	2.58	219
RelSv%	0.22	2.79	219
iGVA/60	1.53	1.28	219
iTKA/60	1.73	0.69	219
Round	1.38	0.49	219

As displayed in Table 3, the regression analysis in *step 1* (i.e., the model containing all nine control variables without draft round) was a significant predictor of playing time, F (9, 209) = 34.38, $p < 0.001$, $R^2 = 0.597$. Interestingly, penalties, injury and player relocation did not have significant effects on TOI. This is likely due to players' on-ice production overriding these three variables in the coaches' decision making process when distributing ice time. Expectedly, offensive metrics (RelxGF/60 and RelSh%) had significant positive effects on playing time. However, defensive metrics (RelxGA/60 and RelSv%) had the opposite effects, where performing worse in these variables resulted in more ice time. This unexpected finding can be explained by observed correlations among variables (unreported in this study), where good offensive performance was correlated with bad defensive performance, likely due to forwards focusing more on their offensive duties and neglecting their defensive responsibilities. This suggests coaches do not penalize forwards for bad defensive performance, as long as they are generating offense efficiently.

With regard to the main independent variable of interest, the inclusion of draft round in *step 2* formed a significant change to the model (Table 3), F (1, 208) = 17.39, $p < 0.001$, $R^2 = 0.031$; meaning draft round added 3.1% of the explained variance in the outcome variable. The final model, which included all 10 predictor variables was significant, F (10, 208) = 35.1, $p < 0.001$, $R^2 = 0.628$. Unstandardized beta coefficients showed that while holding all other variables constant, being selected in the second round as opposed to the first decreased playing time by 0.74 minutes per game, which equates to 44.4 seconds. It is important to note that the 95% confidence interval for the effect of draft round is not narrow (-1.08 – -0.39), which highlights some uncertainty regarding the true population effect. However, the non-inclusion of a zero value, along with meeting the normality assumption and having a sufficient sample size suggest that the point estimate of the beta coefficient (i.e., -0.74) is likely to closely resemble the true population effect (Du Prel et al., 2009).

Table 3. Hierarchical multiple linear regression analysis before and after entering "draft round" as a predictor variable

Variable	Unstandardized beta coefficient (B)	95% Confidence intervals	Standardized beta coefficient (β)	t	Semi-partial correlation (sr)
Step 1					
Constant	10.84**	9.8 – 11.86		20.78	
iPENT/60	0.02	-0.19 – 0.23	0.01	0.19	0.01
Injury	0.16	-0.25 – 0.56	0.04	0.78	0.03
Relocation	-0.34	-0.72 – 0.04	-0.08	-1.79	-0.08
RelxGF/60	2.04**	1.42 – 2.65	0.42	6.54	0.29
RelxGA/60	0.86*	0.26 – 1.46	0.14	2.80	0.12
RelSh%	0.11*	0.03 – 0.19	0.15	2.66	0.12
RelSv%	-0.18**	-0.24 – 0.12	-0.26	-5.61	-0.25
iGVA/60	-0.05	-0.18 – 0.09	-0.03	-0.71	-0.03
iTKA/60	0.56**	0.28 – 0.83	0.20	3.98	0.18
Step 2					
Constant	12.25	11.06 – 13.44		20.22	
iPENT/60	-0.02	-0.22 – 0.18	-0.01	-0.23	-0.01
Injury	0.04	-0.36 – 0.43	0.01	0.18	0.01
Relocation	-0.38*	-0.75 – -0.02	-0.09	-2.06	-0.09
RelxGF/60	1.94**	1.35 – 2.53	0.39	6.45	0.27
RelxGA/60	0.69*	0.09 – 1.28	0.11	2.30	0.09
RelSh%	0.09*	0.02 – 0.18	0.14	2.43	0.10
RelSv%	-0.18**	-0.24 – -0.12	-0.26	-5.79	-0.25
iGVA/60	-0.07	-0.19 – 0.06	-0.05	-1.04	-0.04
iTKA/60	0.50**	0.26 – 0.77	0.18	3.71	0.16
Draft round	-0.736**	-1.08 – -0.39	-0.19	-4.18	-0.18

*$p < 0.05$, **$p < 0.001$

It is also noteworthy to mention that three alternative models were constructed as a robustness check. The first used pick number instead of draft round [*step 1*: F (9, 209) = 34.38, $p < 0.001$, $R^2 = 0.597$; s*tep 2*: F (1, 208) = 24.61, $p < 0.001$, $R^2 = 0.043$; *final model*: F (10, 208) = 36.90, $p < 0.001$, $R^2 = 0.640$]. The second used points scored per 60 minutes (P/60) instead of other advanced analytics [*step 1*: F (4, 220) = 37.65, $p < 0.001$, $R^2 = 0.406$; s*tep 2*: F (1, 219) = 20.91, $p < 0.001$, $R^2 = 0.052$; *final model*: F (5, 219) = 37.03, $p < 0.001$, $R^2 = 0.458$]. The third used total games missed due to injury instead of a dichotomous injury variable [*step 1*: F (9, 207) = 34.49, $p < 0.001$, $R^2 = 0.600$; s*tep 2*: F (1, 206) = 16.79, $R^2 = 0.030$; *final model*: F (10, 206) = 35.09, $p < 0.001$, $R^2 = 0.630$]. Results from these alternative models were all very similar to the one used in this study, and the sunk cost effect was significant in all of them with comparable R^2 values, thereby confirming that our findings are robust.

Discussion

The purpose of this study was to test for sunk cost fallacy in the NHL draft by examining the effect of draft round on playing time. Results showed that after controlling for penalties, injury, being relocated and on-ice performance, the round in which a player was drafted had a significant effect on playing time. Perhaps more important than statistical significance is the practical significance of this effect. We found that, holding all other variables constant, first round draftees play 44.4 more seconds per game than second round draftees. While this may seem as a negligible effect on a game-to-game basis, it becomes sizable as it compounds over time, resulting into 60.68 more minutes played over the course of a full 82-game NHL season. Given that the average forward in our dataset (i.e., an average first or second round draftee in the first five years of his career) plays 11.28 minutes of 5-on-5 per game, a 60.68 minute difference translates into five more games worth of accumulated playing time and experience in a season. Taking this into consideration, we suggest that the sunk cost effect observed in our data is meaningful.

Findings from this research add to an existing body of literature on sunk cost effects in professional sports leagues (Camerer & Weber, 1999; Keefer, 2015, 2017; Leeds et al., 2015; Staw & Hoang, 1995). However, it is difficult to compare the magnitude of these effects across leagues, due to differences in statistical analyses between studies, as well as discrepancies in playing time distribution between sports. Nonetheless, the presence of this effect in this sample is particularly interesting, given two unique aspects of the NHL relative to other sports leagues. First, unlike the NBA and NFL, monetary investment is assumed to be a non-factor during the beginning of NHL players' careers, as the majority of draftees are signed to contracts of standardized values (Collective Bargaining Agreement between National Hockey League and National Hockey League Players' Association, 2013). Yet, despite monetary commitments being similar across draft rounds, sunk cost effects remain. This suggests that it is not *financial expenditure* that drives this effect in hockey; rather, it is the expenditure of a *first round draft pick* to select a player that creates a sunk cost, thereby leading to an escalation of commitment. Second, the NHL has a deeper "farm system" compared to the NBA and NFL (Tingling et al., 2011), which comprises two minor leagues known as the American Hockey League (AHL) and the East Coast Hockey League (ECHL). After selecting players in the draft, NHL teams are able to assign their draftees to these leagues, or temporarily re-assign them to the collegiate or junior teams from which they were originally drafted.[11] It has been hypothesized by prior research – although not tested – that such a deep farm system would nullify any sunk cost effects associated with the draft (Koz et al., 2012; Tingling et al., 2011), given that it provides NHL teams with long-term opportunities to continually assess their prospects' development and performance in order to judge whether they are NHL-caliber or not. Again, however, despite having a farm system and the advantages this provides, the NHL still exhibits sunk cost effects associated with prior selection.

[11] There are a few exceptions that apply. For example, draftees from the Canadian Hockey League (CHL) under the age of 20 are not AHL eligible, and can only be re-assigned to their junior team if they are not NHL-ready. Likewise, collegiate players can only be re-assigned to their college as long as they had not signed a professional contract. Otherwise, they are assigned to the AHL.

Similar to prior studies on the escalation of commitment in professional sports (Camerer & Weber, 1999; Staw & Hoang, 1995), the non-experimental nature of our study only reveals the presence of this effect and not the specific underlying psychological mechanisms driving it. However, literature in this area has identified a plethora of such mechanisms from which we can draw plausible explanations for our results (for a meta-analysis, see [Sleesman et al., 2012]). One of which is self-justification, which suggests decision makers escalate their commitments towards a losing investment in hopes that – over an extended period of time – escalation would cause an eventual turnaround in the outcome, which would then justify the original sunk cost they have incurred (Aronson, 1968). Within the contexts of our study, NHL organizations may provide more playing time to a first round draftee – despite falling short of the expectations of being a superior player than those drafted one round later (i.e., a losing investment) – in hopes that increased ice time would eventually cause said player to reach his expected potential thereby justifying the decision to select him. Through qualitative interviews by Battochio et al. (2016), a first overall NHL draftee noted that although management staff was frustrated with his subpar performance relative to his draft position, they were also inclined to think that he might eventually “break out” over time.

In addition to self-justification, prior research has shown that career and reputational concerns are important motivators of escalation of commitment (Tamada & Tsai, 2014); particularly when “investments” are made public in front of a large audience, inciting a need to “save face” and avoid public embarrassment (Brockner et al., 1981; Ronay et al., 2017). In the NHL, the first round of the draft draws hundreds of thousands of television viewers (Lewis, n.d.), not counting access to draft selections through online sources for an even larger audience of fans and pundits. This may, as a result, drive an organization to escalate its commitment towards a player as an attempt to maintain the reputation of the decision makers involved. It should also be noted that pressures to escalate do not exclusively come from outside sources (i.e., fans and pundits), but from within organizations themselves. Intra-organizational politics can motivate a sunk cost fallacy even in the face of diminishing returns on investment (Guler, 2007), which may lead NHL general managers to exhibit this fallacy when experiencing pressure from the ownership group. Other intra-organizational dynamics may also be relevant to our findings. For example, Sleesman et al. (2012) noted that "de-escalation would be even less likely if it might negatively impact a colleague with a substantial amount of power and status in the organization" (p. 553). This may explain why escalation of commitment was found in our data even though the person responsible for distributing playing time (i.e., the head coach) is not the same person who is responsible for making draft selections; instead, it is the general manager and director of amateur scouting, who hold positions of power within the organization.

While the escalation of commitment is largely studied through the lens of behavioral economics and decision making, we view the implications of our findings from a talent development perspective as well. Given that first round draftees are afforded more opportunities to play and accumulate experience, later draftees may find themselves in a disadvantageous position regarding their development and growth as NHL players. Despite the widely held belief that only training within practice settings is essential for expertise attainment (Ericsson et al., 1993), time spent in competition is a major, yet overlooked, contributor to learning and development (Janelle & Hillman, 2003). In fact, team sport athletes rated competition (i.e., match play) as the most valuable form of training for developing perceptual and decision-making abilities, and highly rated its contribution towards skill execution development (Baker et al., 2003). This is largely due to the fact that in-game settings offer a unique set of challenges (e.g., pressure from fans and viewers, impact of result on standings, play-off elimination, etc.) that are difficult, and sometimes unfeasible, to replicate in practice settings (Baker & Young, 2014).

It is important to note that in order to further our understanding of the implications of sunk cost effects on NHL talent development, similar analyses to ours are needed within minor league contexts. Particularly, in the American Hockey League (AHL), which is a developmental system where NHL teams can assign their prospects after being drafted, in order to continue their maturation process and adjust to the professional demands of hockey. Considering that sunk cost effects have been observed at the NHL level, it is possible that they also exist in the AHL in a similar, if not increasing, capacity. Unfortunately, AHL playing time data is currently proprietary, as NHL general managers are protective of their developmental methods (Pronman, 2017). Should playing time data become available in the future, this would form a beneficial avenue for research to explore. In the meantime, we encourage NHL organizations to investigate this effect in their minor league systems given its implications on the development of their prospects. This is not exclusive to playing time only, but to other forms of "investment" as well, such as individualized coaching or skating sessions, which have been cited by NHL players to be disproportionately distributed among prospects in the developmental system (Battochio et al., 2016).

Limitations

Although the current study makes novel contributions to our understanding of this effect in the NHL, there were notable limitations to our analysis. First, unlike research from other leagues (Keefer, 2015; Kim et al., 2015; Leeds et al., 2015), we only examined the aggregated sunk cost effect over a five year period, as opposed to studying the trend in the magnitude of this effect from year to year. As a result, we cannot make conclusions on how decision makers' commitment towards draftees changes over time. However, this limitation is due to fundamental differences between leagues; NHL draftees take a few years to develop and reach the NHL, which is not the case in the NBA or NFL. In fact, 54 out of 60 players (90%) selected in the 2019 NBA draft played in the NBA the following season, whereas only 5 out of 217 NHL draftees (2%) made their debut in that same time span. Therefore, NHL data does not offer a sufficient sample size to explore this effect independently for each year following the draft.

Second, approximately 27% of the variance in playing time remains unaccounted for by our regression model; therefore, it is possible that some aspects of first round draftees' contribution towards their teams are not captured by the performance metrics used in this study. This is particularly possible for "intangible" contributions such as leadership and positive behaviors conducive to team cohesion (Cotterill & Fransen, 2016). In fact, prior research has shown that certain characteristics – often referred to as "intangibles" in the hockey world – are particularly valued by talent evaluators in the sport, including perceived work ethic, competitiveness, passion, and leadership (Guenter, 2018). Camerer and Weber (1999) raised this point as a limitation of sunk cost effect research in sport settings, indicating that draft order itself may contain some intangible information about the quality of a draftee (i.e., the reason player A was selected before player B is due to better unmeasurable qualities already contained within draft number). In addition to intangibles, NHL teams house their own analytics departments which analyze proprietary performance metrics. As a result, it is likely some teams rely on such metrics to distribute playing time, which our model does not account for as that data is not accessible to the public.

Perspective

The sunk cost effect has been observed in different professional sports leagues, such as the NBA and NFL, whose draft structure offers higher monetary rewards to players selected early than ones selected late (Keefer, 2017). Results from this study suggest this effect also exists in the NHL, despite the fact that contract values are not determined based on draft order. In fact, first round draftees were shown to receive significantly more playing time per game than second round draftees, even after controlling for on-ice performance and other mediators of ice time. This suggests the irreversible decision to draft a player constitutes a sunk cost, which subsequently leads to escalation of commitment. In light of our findings, we argue that this effect may have potential negative consequences of later draftees, given the importance of playing time on the learning and development of athletes. In the same sense, we suggest NHL teams may benefit from conducting intra-organizational exploration of this effect within their minor league systems to ensure optimal developmental environments for their prospects.

Chapter Five

General Discussion

General Discussion

The purpose of this dissertation was to thoroughly examine the efficacy of talent selection and development in the National Hockey League (NHL) draft. Chapter one provided a comprehensive overview of the literature pertaining to talent selection in North American professional sports. It was evident from this literature review that research pertaining to draft and development in the NHL is rather scarce and relies on outdated data that may not represent contemporary practices. As such, the remaining chapters aimed to address some of these gaps using modern data and analytics. Chapter two examined the accuracy of NHL talent selection by constructing indices of offensive and defensive performance, and retrospectively comparing these indices across draft rounds from 2007-2014. The results showed substantial inaccuracies in the draft and indicated that further examination of the underlying inefficiencies in selection are necessary. To this end, chapter three included a thorough analysis of the overlap between the predictors of draft order and future NHL success. Findings from this chapter uncovered a wide variety of player attributes that teams tend to overvalue, and undervalue, at the draft. While chapters two and three showed substantial evidence of draft inefficiencies, it was important to recognize that such inaccuracies do not only stem from inadequate scouting or player evaluation methods; rather, talent development plays a crucial role in whether a draftee fulfills his projected potential. To investigate this effect, chapter four examined how teams distribute developmental opportunities – as measured by playing time – among their draftees, and whether that distribution is affected by sunk cost bias.

The following sections describe the findings from this dissertation, and elaborate on the implications they have for (a) practitioners (i.e., scouts and other player evaluation personnel), and (b) researchers in the talent identification and development field.

Key Findings

Chapter Two

The first study of this dissertation examined the accuracy of NHL draft selections. Findings revealed that forwards drafted in picks #1-15 (lottery picks) outperformed their peers drafted in picks #16-31 (non-lottery picks) offensively, yet there was no significant difference between the two groups' defensive performance. For defensemen, there were no significant differences between lottery and non-lottery picks for either offensive or defensive measures.

When examining selection accuracy throughout the entirety of the draft, results showed forwards drafted in round 1 outperformed those drafted in round 2, and those drafted in round 2 outperformed their peers drafted in round 3. After round 3, however, there were no significant differences in future NHL performance between rounds. Similarly, defensemen selected in round 1 outperformed their peers drafted in round 2, but from that point forward no inter-round differences were observed. Findings from both forwards and defensemen suggest substantial inaccuracies in selection. Moreover, they indicate NHL teams are only able to identify the best of the draft class (i.e., first round or two), but have difficulty distinguishing between the rest of the prospects.

Chapter Three

The second study investigated which performance metrics, anthropometric/demographic measures, and text-mined attributes are over/under valued in the draft. The following are the findings from each of these data categories.

Performance Metrics

In the forwards group, results suggested CSB rankings, GP, and NHLe PPG were valued appropriately in the draft, as their influence on draft order matched their effects on NHL success.

However, NHL decision makers were found to overvalue penalty minutes, and undervalue plus/minus in their selection processes. For defensemen, NHLe PPG and plus/minus were valued appropriately. In contrast, NHL teams overvalued CSB rankings in their selections, as this variable was not predictive of future performance despite its significant influence on draft order.

Anthropometric/Demographic Measures

For forwards, NHL teams appeared to value weight appropriately in their selections; however, they overvalued height by drafting taller players earlier despite this variable having no impact on career success. Similarly, teams overvalued age by drafting younger players earlier, yet such players did not go on to have better careers. Amongst defensemen, age and weight were neither significant predictors of draft order nor career success. Height was found to be a significant predictor of draft order; however, contrary to forwards, taller defensemen did go on to achieve more NHL success, suggesting a more accurate valuation of this variable.

Text-Mined Attributes

In the forwards sample, NHL teams valued *passing and playmaking ability* more accurately by drafting players with this quality earlier, who then went on to have more NHL success. However, NHL teams overvalued *lack of physical strength*, and undervalued *board battles*, *backchecking ability*, and *hockey sense*. With defensemen, NHL teams undervalued *passing and playmaking ability*, and undervalued *lack of physical strength* as well as *work ethic and leadership* in their draft selections.

Chapter Four

The third, and final, study of the dissertation aimed to evaluate the efficacy of NHL talent development past the point of selection, by examining subsequent playing time of draftees based on their selection order. Results from this analysis showed that forwards selected in the first round receive significantly more playing time than second round draftees, even after controlling for on-ice performance, injury, and trades. In fact, first round draftees receive over 60 minutes of total ice time throughout the course of a full NHL season, which equates to five more games worth of experience per year. Considering that playing time has been linked to enhanced perceptual-cognitive ability and skill execution proficiency (Baker et al., 2003; Gabbett et al., 2009), these findings suggest that later-round draftees are at a substantial developmental disadvantage compared to their first round peers.

Implications

Findings from all three studies of this dissertation have implications for both researchers and practitioners (i.e., NHL talent identification and development personnel). The following is an extended discussion of those implications.

Practical Implications

In light of the major selection inaccuracies highlighted in Chapter 2, NHL teams may benefit from expanding the scope of their player evaluation to include psychological measures that have been empirically linked with better future performance. One of such psychological attributes is competitive anxiety management, which refers to athletes' ability to not only maintain composure under competitive pressure, but to also view anxiety as facilitative towards sport performance (Neil et al., 2012). For instance, Butt et al. (2003) found a significant positive relationship between field hockey players' anxiety interpretation and performance. In addition, elite and non-elite swimmers were shown to experience similar intensity levels of anxiety prior to performance; however, the elite group had higher confidence and reported a facilitative view of anxiety, while the non-elite group reported lower confidence and a debilitative perspective of anxiety (Jones et al., 1994). Such results were later replicated in rugby players (Neil et al., 2012).

In the case of NHL talent selection, teams may benefit from extracting such data through the combine process by administering certain tests as part of the draft combine, such as the Achievement Anxiety Test (AAT) and Sport Confidence Inventory (SCI), both of which have been validated in the literature (Couch et al., 1983; Frischknecht et al., 2016; Jones et al., 1994; Wine, 1980).

Similar to competitive anxiety management, other psychological attributes such as Self-Regulated Learning (SRL) have been identified as predictors of performance. SRL is largely grounded in metacognition (i.e., thinking about one's own thinking and learning processes) and is defined as "learners' awareness and control of their thoughts, actions, emotions, and motivations in the pursuit of goals" (Zimmerman, 1986, as cited in McCardle et al., 2019, p.113). As such, many components of SRL – such as reflection, planning, goal-setting, self-monitoring, etc. – have been shown to differentiate between elite and non-elite athletes (Jonker et al., 2012; Toering et al., 2012; Toering et al., 2009). Since the transition between junior and professional hockey requires adaptations to markedly different learning demands, testing for components of SRL – either through interviews or by using scales such as Self-Regulation of Learning Self-Report Scale (SRL-SRS) – may be of relevance to NHL teams at the draft. Moreover, using SRL interventions to improve the learning/development of prospects once they are drafted may also yield benefits (for an extensive review, see McCardle et al., 2019).

Findings also had implications related to decision-making, in particular, regarding cognitive biases in selection. While draft inaccuracies are in-large due to the inherent difficulty of predicting the future, there may be certain biases that further exacerbate this challenge by clouding scouts' judgement of players. The following is a selection of biases that have been identified in the decision-making psychology literature, followed by a hockey-specific example to illustrate their manifestation in the NHL draft and, lastly, some suggestions to reduce their effects.

Availability heuristic

This bias describes the tendency to draw conclusions regarding an individual based on the first memory – or set of memories – that come to mind. Often, these memories come from events of substantial magnitude as these are particularly more memorable and easily recalled (Tversky & Kahneman, 1973).

Example: NHL draft-eligible prospects often compete in high-profile tournaments that take place before the draft (e.g., World Juniors, Hlinka Gretzky cup, etc.). When asked to rate a player – or form an opinion on him – at draft meetings, a scout's judgement may be influenced by memories from those tournaments, as they are of high importance and may be easier to recall (e.g., the player scored a goal in the final game, thereby labeling him as a "clutch player"). While performance in high-profile tournaments is indeed important to take into consideration, one should be cautious as to whether such moments actually represent the overall quality of the player and how he performs on a consistent basis. To minimize the impact of this heuristic, teams could benefit from designating one member of the scouting department to act as a "devil's advocate", in which their role is to challenge other scouts to defend their judgement of players and provide strong evidence for their beliefs. Another beneficial strategy for combatting the availability heuristic is to cross-reference a scout's opinion of a player with empirical data from the analytics department, as such data often revolves around a player's average performance (i.e., regression to the mean) and is therefore more representative of a player's output on a consistent basis.

Order effect

This bias describes the influence of the order in which information is presented on one's judgement (M. J. Smith et al., 2009). This bias can be further broken down into two main effects: (1) primacy effect – which describes the tendency to rely heavily on the first piece(s) of information presented to the observer when making judgements (Sullivan, 2019). In other words, one becomes "anchored" on first impressions, and fails to adjust one's beliefs appropriately despite emerging information; (2) recency effect – which, contrary to primacy effects, refers to one's judgement being overly influenced by the last piece of information presented, while overlooking prior information (Kalm & Norris, 2018).

Example: consider a scout, or video analyst, who is tasked with breaking down a junior player's shifts from a particular hockey game. The player performs poorly in his first shift – or first few shifts – but manages to improve as the game goes on. Despite subsequent improvements, the scout may be anchored on the poor performance shown earlier in the game, causing him to give the player a lower rating than what his actual overall performance would indicate. Contrarily, a player may end his junior season with a much stronger performance than his season average, thereby causing the scout to overvalue his overall performance and, subsequently, his position in the draft.

To combat this bias, it is recommended to delay the time between receiving information on a subject (i.e., player, candidate, etc.) and making a judgement (Greenlees et al., 2007; McKelvie, 1990), as this would one to integrate varying pieces of information into the decision making process, and alleviates the influence of order on the overall judgement. This "delayed intuition", as termed by Kahneman (2011, p.124), was also found by the author to be a useful tool in substantially improving military selection accuracy.

Groupthink

This effect describes the tendency to adhere to the collective thinking of the group, and to refrain from voicing disagreements for the sake of harmony and group cohesion (Janis, 1972, 1982).

Example: in this scenario, the general consensus in the draft "war room" is to draft a certain player with pick #5, with the exception of one scout who thinks another player would be a more wise selection. This scout may be inclined to reserve their disagreement in fear of standing out, creating conflict, or disrupting the harmony of the group. In turn, this may lead the team to make the selection without critically evaluating both sides of the argument for selecting him. To minimize the prevalence of groupthink, leaders within NHL organizations are encouraged to create a culture where scouts are encouraged to voice their disagreements, and feel safe to engage in constructive conflict without fear of disrupting group harmony or losing "group identity" (Farah & Baker, 2020b; Turned & Pratkanis, Anthony, 1997).

Halo effect

This last bias describes the effect where an evaluator's judgement of a specific characteristic/trait becomes biased by their evaluation of a completely separate and unrelated trait (Gibson & Gore, 2016; Palmer & Feldman, 2005).

Example: this effect may be especially common when evaluating psychological attributes, as opposed to technical/tactical skill. As shown in Chapter 3, if a player has a good work ethic, a scout's judgement of his leadership may also be positively skewed. This is despite the fact that leadership is a completely separate construct from work ethic, and is comprised of different components. To avoid the halo effect in scouting, teams are encouraged to use strict player evaluation criteria where each criterion is given an explicit definition and is comprised of a definitive list of associated components (Den Hartigh et al., 2018). By doing so, the organization will be able to make it explicitly clear to the scouts which component contributes to which criteria, and may, therefore, minimize the chance of a scout confounding their judgement of two separate criteria.

Draft Inefficiencies

After testing the accuracy of the draft in Chapter 2, it was important to further investigate the sources of draft inefficiencies in the following chapter, from which there are two main practical implications to draw. First, by highlighting player attributes that are over/under valued at the draft, NHL decision makers can use this information to evaluate their selection processes. As mentioned in Chapter 3, however, due to the novelty of our text-mining approach and findings, we recommend practitioners interpret and apply our results with caution as replication and extension are needed to solidify our results. Therefore, instead of drafting more players with undervalued attributes, or fewer players with overvalued ones, we suggest NHL teams should use the information presented in this study to reflect on their own player evaluation criteria, examine whether some of the inefficiencies are indeed present in their selections, and decide whether making adjustments is logical within the contexts of their overall selection processes.

Second, perhaps the most notable practical implication of the current research does not lie in uncovering inefficiencies in NHL teams' *valuation* of attributes in their selection process; rather, it is in uncovering inefficiencies in scouts' *evaluation and measurement* of such attributes. The talent identification literature suggests there are generally two types of judgement involved in talent evaluation: clinical and actuarial (Den Hartigh et al., 2018). Clinical judgement is characterized by forming an *overall impression* of the player in a scout's mind, which is typically constructed using implicit criteria and subjective preferences of player types, without assigning weights to different attributes of a player's overall game (Christensen, 2009; Lath et al., 2021). In contrast, actuarial judgement is characterized as an *independent evaluation* of each attribute of a player, formed using explicit criteria and objective/empirical associations between current and future performance, while assigning weights to different attributes depending on their importance (Johansson & Fahlén, 2017; Musculus & Lobinger, 2018).

Clinical judgement, despite being the most common form of judgement in talent evaluation (Den Hartigh et al., 2018), is problematic as it requires piecing together many variables (i.e., attributes) at once despite the deficits in the human mind's ability to do so (Kahneman, 2011b; Kahneman & Frederick, 2002), and leads one to fall victim to numerous cognitive biases (halo effect, availability bias, order effects, etc.). In the current research, it is evident hockey scouts rely predominantly on clinical judgement as many of its characteristics are consistently observed throughout the scouting reports. For example, the use of implicit criteria is evident as *inconsistency in effort and performance* is only evaluated in 21% of the reports, and *defensive awareness* is only evaluated in 30% of the reports. If evaluation criteria were explicit, all players – or at least the vast majority – would have been rated on these attributes as opposed to only a select few. Likewise, 11 out of 13 extracted attributes in Study 2 had positive connotations, which would not be the case had a set of neutral criteria been constructed prior to conducting the evaluation.

Another example of observed clinical judgement is that the word "vision" appeared to cross-load[12] on three attributes: *hockey sense, passing and playmaking ability*, and *soft hands*; yet these three attributes describe separate areas of a player's performance. If criteria were explicit,

[12] In factor analysis, cross-loading refers to a single variable having a strong relationship with two different factors. In our case, when one item (word) is an important part of two separate constructs (player attributes).

and each attribute was evaluated according to a definitive list of characteristics – as actuarial judgements would suggest – a player's vision would only contribute towards his rating on one specific attribute. Last, *work ethic and leadership* was one of the extracted attributes, suggesting scouts view both concepts as one attribute. This may reflect a halo effect[13] caused by combining multiple variables without a set structure, as sport leadership is its own psychological concept comprised of a set of characteristics (Cotterill & Fransen, 2016; Loughead, 2017; Maechel et al., 2020), that are conceptually unrelated to a player's work ethic.

Contrary to clinical judgement, actuarial judgement has been shown to yield more accurate predictions due to its objective and rigorous nature (Kuncel et al., 2013; Lindsay & Beail, 2004). However, in order to follow an actuarial judgement process, three standards should be met (Musculus & Lobinger, 2018): (a) objectivity: the extent to which evaluation criteria explicitly outlined and defined; (b) reliability: the consistency in which a scout is able to measure different players' attributes, as well as the consistency in which different scouts are able to evaluate the same player (inter-rater reliability); and (c) validity: the degree to which currently observed and evaluated attributes relate to future performance. Keeping these three pillars in mind, the following is a brief guideline on how scouts could transition from clinical to actuarial methods of judgment in their player evaluation processes:

1. *Determining valid attributes* – in this step, scouts' input is needed on which attributes they value in a player; similarly, empirical research from analytics departments or consulting agencies is required to determine which attributes are transferrable from pre-draft leagues to the NHL (Putrino et al., 2021). The overlap between the two could then

[13] Halo effect describes the phenomenon wherein an evaluator's judgement of one trait proportionately skews their judgement of an entirely separate trait (Gibson & Gore, 2016; Palmer & Feldman, 2005).

be used to construct a list of explicit criteria on which players are tracked and evaluated (Johnston, Farah, & Baker, 2021).

2. *Setting clear terminology* – the basis of a sound actuarial judgement is objectivity, and the basis of objectivity is clear and direct definitions of attributes (Musculus & Lobinger, 2018). In many cases, however, each scout may have a different definition for the same attribute (see *hockey sense*, for instance, in the discussion section of Chapter 3); subsequently, measurements of the same attribute may differ from one scout to another, which causes inter-rater reliability of the evaluation process to suffer as a result of this noise (Kahneman et al., 2021). Therefore, it is important that all scouts within an NHL club use the same terminology when describing players. To achieve this uniformity in language, the scouting department should collectively work to define each attribute identified in step 1, preferably with the help of the team's sport psychologist for certain attributes (e.g., resilience, leadership, etc.) (Musculus & Lobinger, 2018).
3. *Identifying components of criteria* – After setting definitions, behaviors – or components – associated with each attribute should be explicitly identified to help the scouts recognize, and reliably measure, an attribute when they observe it during a game. For example, should *hockey sense* be a criterion of interest, this attribute could be broken down into separate components (such as positional awareness, reaction time, anticipation ability, ability to read plays, etc.). This step also prevents confounding effects from the measure of other attributes, as in the above-mentioned case of "vision" being a behavior associated with three different attributes.
4. *Setting a scale* – After identifying an explicit list of criteria and assigning clear definitions, the next step is to construct a measurement approach. To do so, it is

recommended that a rubric be followed for grading each attribute, with a specific scale (e.g., 1-5, 1-10, etc.) (Den Hartigh et al., 2018).

5. *Determining weights* – Following the construction of the rubric, it is important to determine how important each criterion (i.e., attribute) is to the overall evaluation of the player (Johnston, Farah, & Baker, 2021; Jokuschies et al., 2017). In other words, will each attribute hold the same 'weight' (e.g., are skating and hockey sense equally important?)? Similarly, will each component of a particular attribute hold the same weight (e.g., are acceleration speed and agility equally important in evaluating skating?)? When selection criteria are set without assigning weights to variables, the risk of inconsistent selections over time increases, which may result in exacerbating draft inefficiencies.
6. *Performing the measurement* – If possible, each attribute of a player should be evaluated one at a time (Den Hartigh et al., 2018), which may be easier in video scouting – where replay is an option – than real-time scouting. Furthermore, each component of an attribute (see step 3) should be evaluated and scored, then a player's total score can be obtained by adding component scores and their assigned weights.

To ensure the reliability of measurement between evaluators, more than one scout should ideally evaluate the same player. However, if that is not possible, it would be beneficial for at least one scout and one other expert (e.g., director of scouting, cross-checker, etc.) to cross reference their evaluations. That said, it is important the two evaluators assess the player independently without prior discussion of his strengths and weaknesses, to avoid influencing one another's judgement before observation.

Talent Development

While the first two studies investigated draft accuracy, the final study shifted the focus of the dissertation to the efficacy of draftees' development past their selection. Results from Chapter 4 highlighted that sunk cost effects lead NHL teams to disproportionately distribute playing times in favor of their first round draftees. Given the importance of playing time on talent development, this finding has multiple implications for stakeholders. First, our study revealed that a general trend exists in the league but did not identify which teams are most – or least – affected by sunk cost effects. Therefore, teams may benefit from conducting independent evaluations of their organizations to study the extent to which they are affected by this fallacy. This, in turn, may give decision makers (coaches, general managers, etc.) evidence to determine whether their playing time distribution strategy needs adjustment. Second, teams should investigate other ways developmental opportunities (i.e., besides playing time) may be disproportionately allocated. For instance, every NHL organization has a "player development" department that is responsible for tracking, evaluating, and advancing multiple facets of a drafted prospect's development (technical, tactical, psychological, social, etc.). This department often conducts its operations through video sessions, on-ice sessions, visits to the drafted prospect's junior/collegiate team, etc. In light of our findings, we recommend teams evaluate whether first round draftees benefit from more coaching sessions and developmental attention than later draftees due to sunk cost effects, as been suggested to be the case by an anonymous former first round prospect (Battochio et al., 2016).

Research Implication

Considering that selection accuracy was found to be stronger in the beginning of the draft (rounds 1 and 2) and lower in the middle-to-end of the draft (rounds 3-7), it is likely that as the draft progresses, the talent pool becomes much more homogenous in perceived skill and ability. As a result, a future avenue of research may be to study the specific predictors of future performance that exist in these two sections of the draft separately, and identify which particular attributes may differentiate successful future performers from the rest of the seemingly homogenous group in the later rounds. Furthermore, much of draft-related research focuses on examining *pre-draft* predictors of performance, which leaves a strong need for researchers to study *post-draft* predictors of NHL success. Such predictors include the number of opportunities a prospect is given to play in the NHL (i.e., “call-ups”), playing time in the league to which he is re-assigned to after being drafted (e.g., major junior, college, etc.), as well as the nature of playing time the player receives in those leagues (e.g., 5v5, power play, penalty kill, 6v5 while trailing at the end of games, etc.). Such research would inform NHL teams of appropriate developmental practices that should be followed in order to give their draftees the best chances of becoming successful NHL players.

In regard to Chapter 3, the novelty of our text-mining process necessitates replication in order to solidify our results. Therefore, we encourage talent identification researchers to test the replicability of our findings by either (a) using reports from different scouting agencies, (b) including a different set of draft classes in the analyses, or (c) a combination of the two. Moreover, we suggest future research could benefit from including more variables into their prediction models to expand our knowledge of draft inefficiencies. This includes pre-draft advanced analytics, combine data, psychological test scores (if obtainable), and other potential predictors of future performance.

Lastly, in light of findings from Chapter 4 on the prevalence of sunk cost effects in the NHL, we suggest several research avenues that could further our understanding of this effect.

First, as mentioned in Chapter 2, hockey does not have a universal measure of performance that is widely used (e.g., there is no equivalent to 'Wins Above Replacement' in baseball), and the definition of "successful performance" often varies depending on the researcher's discretion. Therefore, future research may benefit from testing the reliability of our results by using other performance outcomes than the ones chosen in our model. Likewise, future studies may benefit from using different statistical analyses, such as Regression Discontinuity (RD) or other forms of regression analyses, to test the consistency of findings. This would, in turn, contribute to examining the robustness of this effect in NHL settings.

Second, should American Hockey League (AHL) playing time data – which is currently proprietary – become publically available, future studies would benefit from conducting similar analysis in AHL contexts as the majority of NHL players' early development takes place in that league. In the meantime, forging strong research partnerships with NHL organizations may be a useful avenue through such data can be obtained.

Third, in addition to the quantitative statistical analyses proposed above, qualitative research is needed to study the experiences of draftees throughout the developmental system. In particular, it would be useful to explore how draft order shaped and influenced players' developmental opportunities. Given that current prospects are more difficult to reach, former players may be a more attainable sample for these studies to recruit.

Conclusion

In a league in which free agency signings and trades are limited by the salary cap constraints, the importance of drafting and developing successful NHL players has become more important than ever. Yet, there remains a paucity of empirical research examining these processes in hockey. To that end, this dissertation aimed to explore these understudied areas in the literature. Results from all chapters highlighted substantial room for improvement in both player evaluation and player development strategies, and emphasized the need for continued research attention to this league by those in the talent identification and development field. In addition, several practical implications were drawn from each study, and numerous data-driven recommendations were made. Most importantly, however, the work presented in this dissertation highlighted a great need for collaboration between NHL practitioners and researchers to ultimately improve this vital component of NHL organizations' success.

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Appendices

Appendix A. NHL Draft Selection Order

To determine the order of selection among member teams in the entry draft, the NHL uses the following multi-step process (“Hockey Operations Guidelines”, n.d.):

1. Selections #1 to #15: all 15 teams that did not qualify for the playoffs in the previous season enter a lottery, in which each team’s odds of winning the first overall selection are inversely weighted by their position in the standing (i.e., their total regular-season points) as seen in Table A1. After the winner of the first overall draft pick is determined, the odds of the remaining teams are adjusted to decide the winner of the 2nd overall pick, and then adjusted once again for the 3rd overall selection. The remaining 11 teams that did not win the lottery simply receive picks #4 to #15 in reverse order of the regular season standings, wherein the team with the lowest number of points selects 4th, second lowest selects 5th, and so on (“How Does the NHL Draft Lottery Drawing Work?” 2019).
2. Selections #16 to #23: include teams that qualified for the playoffs, but did not finish first in their division or win qualify for the conference finals, in reverse order of their regular season points.
3. Selections #24 to #27: include teams that finished first in their division but did not qualify for the conference finals, in reverse order of their regular-season points.
4. Selections #28 and #29: awarded to the teams that lost in the Eastern and Western conference finals, in reverse order of their regular-season points.
5. Selection #30: awarded to the runner up of the Stanley Cup finals
6. Selection #31: awarded to the Stanley Cup winning team

The same order of selection listed above is then repeated throughout the remaining six rounds. For example, a team that selects 5th in the first round will also receive the 5th pick of the second round (i.e., the 36th pick of the draft).

Table A1

Odds of winning the first overall draft selection weighted by position in the standings

Position in the regular-season standings	Odds of winning draft lottery
17th	1%
18th	1.5%
19th	2%
20th	2.5%
21t	3%
22nd	3.5%
23rd	5%
24th	6%
25th	6.5%
26th	7.5%
27th	8.5%
28th	9.5%
29th	11.5%
30th	13.5%
31st	18.5%

Appendix B. Factor Extraction

Three approaches were taken to guide factor extraction. The first was Kaiser's criteria of retaining only factors with Eigenvalues of 1 or more (Kaiser, 1960). This specific threshold is based on Kaiser's interpretation of the Kuder-Richardson formula 20 (Kruder & Richardson, 1937) which tests the internal consistency of items within a single measurement and the parallel form reliability associated with it. Based on Kaiser's interpretation, any Eigenvalue less than 1 suggests the factor scores have negative reliability, and values over 1 indicate that a factor is reliable (Kanyongo, 2006). As can be seen in Tables B1 and B2, only factors 1 and 2 yielded Eigenvalues greater than 1. In addition, both factors explained a cumulative 72.9% and 64.3% of the variance in forwards and defensemen, respectively, which was above the sufficient threshold (Hair et al., 2014).

Table B1
Eigenvalues and total variance explained by factors – Forwards

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.09	44.20	44.20	2.77	39.58	39.58
2	2.01	28.72	72.92	1.70	24.25	63.83
3	0.72	10.22	83.14			
4	0.67	9.53	92.68			
5	0.21	3.05	95.72			
6	0.18	2.54	98.26			
7	0.12	1.73	100.00			

Table B2

Eigenvalues and total variance explained by factors – Defensemen

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.47	35.27	35.27	2.06	29.49	29.49
2	2.03	28.98	64.26	1.72	24.54	54.03
3	0.99	14.16	78.42			
4	0.68	9.73	88.14			
5	0.48	6.86	95.00			
6	0.19	2.64	97.64			
7	0.17	2.36	100.00			

The second approach was using a scree plot (Figures B1 and B2), wherein Eigenvalues are plotted on the Y-axis and the factor number is on the X-axis. This is often used as a supplementary tool in addition to raw values (Tables B1 and B2), as it displays the exact point at which the steep decline in Eigenvalues meets the flattening line of factors that do not explain much variance (Woods & Edwards, 2011). This particular location is referred to as the "inflection point" and is highlighted in red in both figures. Factors observed before the inflection point should be retained while the remaining ones should be discarded (Field, 2009). Subsequently, the scree plot below suggests only retaining factors 1 and 2, which is in compliance with the first approach discussed above.

The third and final method applied to factor extraction was using researcher judgement to review the latent structures and their contents. Theoretically, the ultimate purpose in hockey is to outscore the opposition in order to win. In that sense, an NHL player's contribution to the team – in terms of *tangible* on-ice performance – can be reduced to his ability to generate scoring chances in the offensive zone and prevent scoring chances against in the defensive zone. Both of these elements were represented in factors 1 and 2 respectively.

Figure B1

Factor analysis scree plot – Forwards

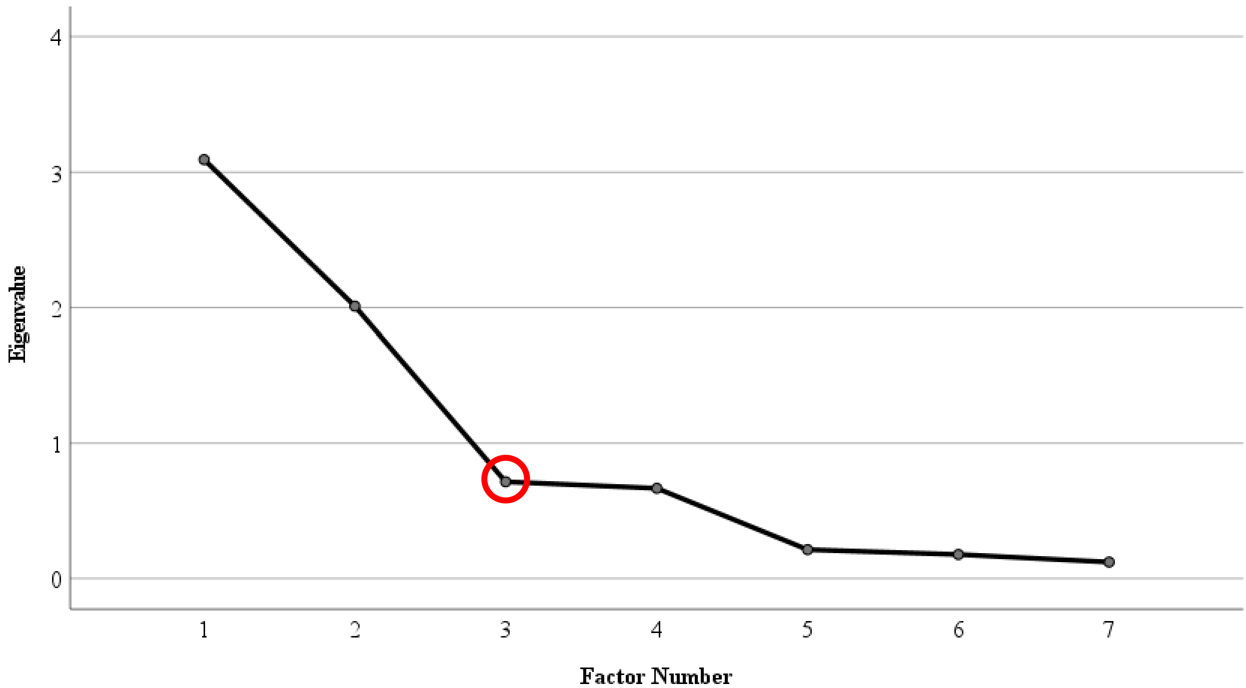
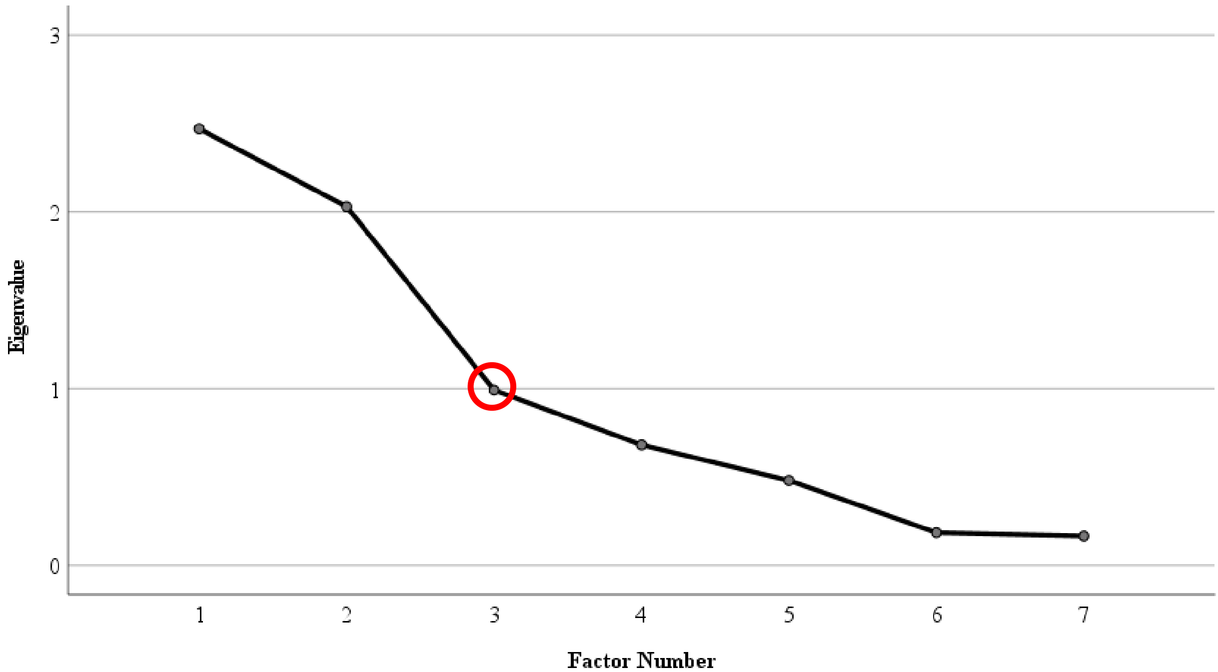


Figure B2

Factor analysis scree plot – Defensemen



Appendix C. League-Specific Translation Factors

Draft-eligible prospects are selected from different leagues across North America and Europe, which have varying degrees of competition level. For instance, some prospects are drafted from the Ontario hockey League (OHL), where players are aged 16-21, while others are drafted from the Kontinental Hockey League (KHL), which does not have a maximum age limit and allows 17 year old players to compete against players in their late twenties or thirties. This disparity in competition levels means one cannot compare scoring rates of an OHL draft-eligible player – who competes against teenagers – to that of a KHL player – who competes against grown men – without first equalizing the playing field.

To do so, Vollman (2014) constructed translation factors to estimate how players' scoring rates would translate to the NHL from their respective leagues. The following procedure was used to arrive at each league's translation factor: a) players' pre-draft data was normalized by dividing their point totals over their league's goal-per-game average, then multiplying the outcome by the league's goal-per-game average from the previous season, b) the first step was repeated for every player in both pre-draft leagues and the NHL, c) every player's points-per-game (PPG) from the NHL was divided over their PPG from their pre-draft league, d) the average of all players from each league was calculated, resulting in a league-specific translation factor (see Table C1). To arrive at a player's NHL Equivalency Points Per Game (NHLe PPG), his raw PPG is multiplied by his league's translation factor.

Table C1
League-specific translation factors

Pre-Draft League	Translation Factor
United States High School-Minnesota (USHS-MN)	0.07
United States High School-Preparatory (USHS-Prep)	0.07
United States High School-Wisconsin (USHS-WI)	0.07
Unites States High School-Michigan (USHS-MI)	0.07
British Columbia hockey League (BCHL)	0.11
Alberta Junior Hockey League (AJHL)	0.12
Molodezhnaya Hokkeinaya Liga (MHL)	0.15
2.Bundesliga (2.Gbun)	0.16
Eastern Collegiate Athletic Conference (ECAC)	0.23
J20 SuperElit	0.25
Quebec Major Junior Hockey League (QMJHL)	0.26
Junior Elite Finish League (Jr. A SM-Liiga)	0.26
United States Hockey League (USHL)	0.27
Western Hockey League (WHL)	0.27
Finish Elite League (SM-Liiga)	0.29
Vysshaya Hokkeinaya Liga (VHL)	0.31
Ontario Hockey League (OHL)	0.32
Central Collegiate Hockey Association (CCHA)	0.32
Hockey Allsvenskan	0.36
Czech Extraliga	0.36
HokeyEttan (Swe-1)	0.36
Hockey East	0.37
National League (NLA)	0.40
Western Collegiate Hockey Association (WCHA)	0.44
American Hockey League (AHL)	0.47
Deutsche Eishockey Liga (DEL)	0.52
Swedish Elite League (SEL)	0.60
Kontinental Hockey League (KHL)	0.80

Appendix D. Central Scouting Integrator (CESCIN)

The Central Scouting Bureau (CSB) releases separate rankings for players competing in North American and European leagues. Therefore, it is important to form a unified list in order to include both types of players simultaneously in one analysis. To do so, Fyffe (2011) constructed a model integrating both CSB lists – known as the Central Scouting Integrator (CESCIN) – which has been used extensively in prior hockey research (M. Schuckers & Argeris, 2015; Vollman et al., 2016). The CSCIN uses historical draft records to form linear prediction equations between past players' CSB rankings and their actual draft order, while accounting for their pre-draft league. The result of these linear equations is a coefficient that is associated with each player given his CSB ranking and whether he competes in a North American or European league.

Table D1 displays Fyffe's (2011) coefficients. For example, if a prospect competes in the United States Hockey League and has a CSB ranking of 21, his ranking would be multiplied by 1.35 and rounded down, to arrive at his CESCIN score of 28. Similarly, a European player whom is ranked 5th by the CSB, would have a CESIN score of 31.

Table D1
CESCIN coefficients for CSB rankings

Location of pre-draft League	CESCIN coefficient
European	6.27
North American	1.35

Appendix E. Distribution of NHL Games Played

Figure E1

Distribution of the outcome variable in part #2 (NHL GP) for forwards

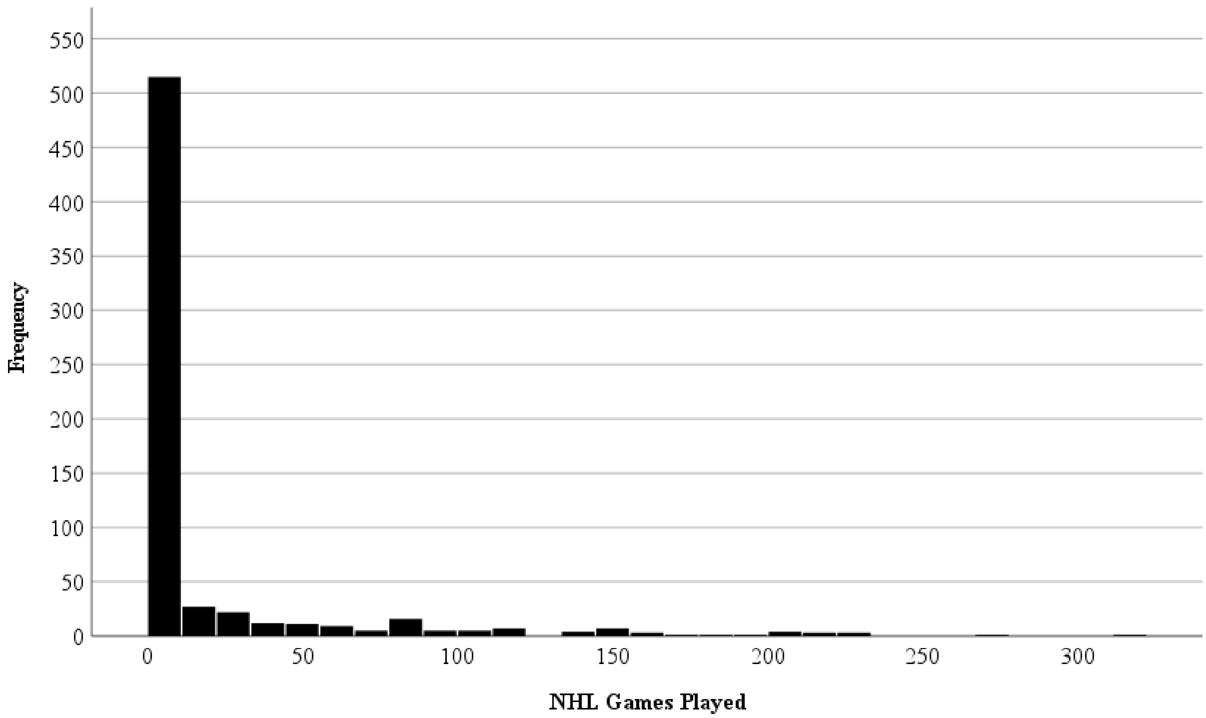
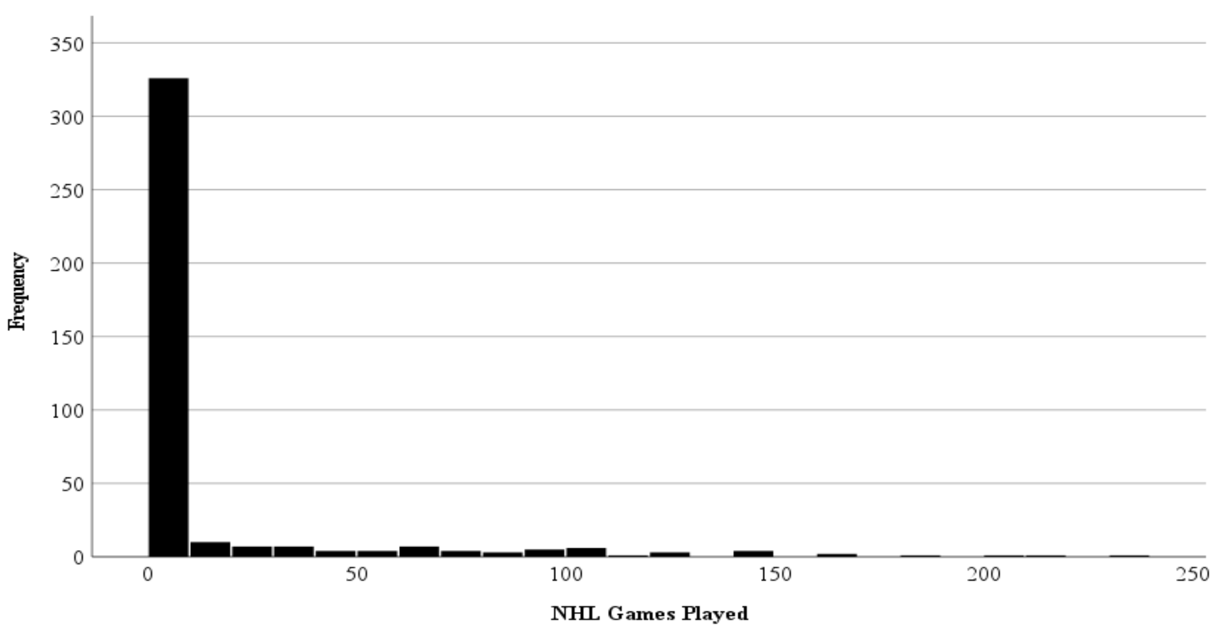


Figure E2

Distribution of the outcome variable in part #2 (NHL GP) for defensemen



Appendix F. Text-Mining Exclusion List

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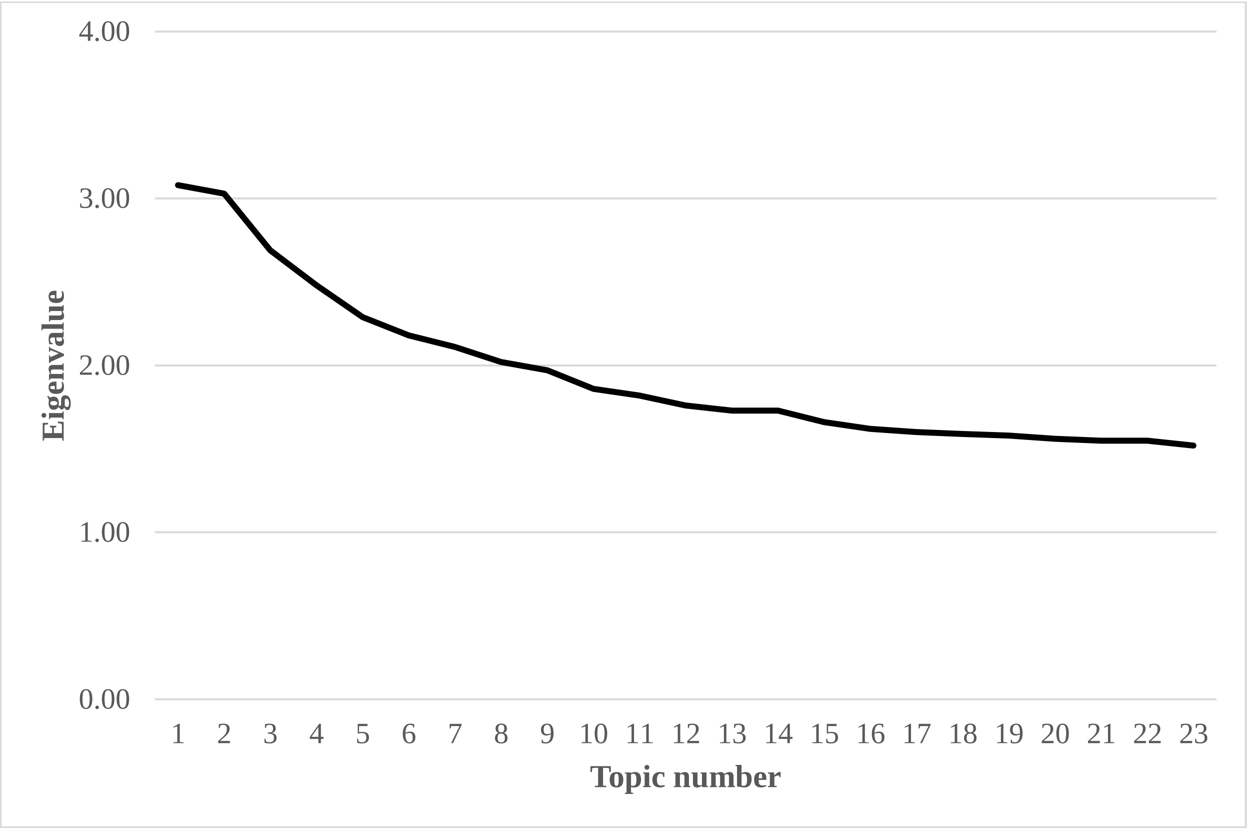
Appendix G. Topic Modelling Scree Plot

Figure G

Scree plot of eigenvalues versus topic number



Appendix H. Correlation Coefficients Between Multiple Linear Regression Variables

Table H1

Correlation coefficients between independent and dependent variables – forward sample

	Draft pick number	CESCIN-adjusted CSB ranking	Height	Weight	Age
Backchecking ability	-0.04	0.01	-0.10	-0.01	-0.05
Hockey sense	-0.07	0.04	-0.10	-0.12	0.02
Inconsistency in effort &	-0.08	-0.11	0.07	0.02	-0.05
Lack of physical strength	-0.11	-0.02	-0.06	-0.29	0.01
Passing & playmaking	-0.16	-0.05	-0.18	-0.20	0.06
Shooting ability	-0.12	-0.07	0.05	0.05	-0.02
Soft hands	-0.10	-0.08	-0.06	-0.09	-0.03
Willingness to fight	-0.08	-0.04	0.10	0.16	0.04
Work ethic & leadership	-0.01	0.02	-0.08	0.00	0.00
Board battles	-0.10	-0.03	0.23	0.22	-0.07
Puck protection ability	-0.10	-0.03	0.14	0.14	-0.02
Defensive awareness	-0.03	-0.01	-0.01	-0.01	-0.08
Shot blocking ability	-0.01	0.10	0.02	0.01	-0.05
Plus/minus	-0.17	-0.01	-0.16	-0.08	0.04
PIMs/GP	-0.10	0.03	0.14	0.31	0.03
NHLe PPG	-0.34	-0.05	-0.26	-0.08	0.16
GP	-0.09	-0.06	-0.14	-0.01	0.03
Age	0.26	0.41	-0.11	-0.01	1.00
Weight	-0.05	-0.02	0.57	1.00	-0.01
Height	-0.11	-0.10	1.00	0.57	-0.11
CESCIN-adjusted CSB	0.39	1.00	-0.10	-0.02	0.41
Draft pick number	1.00	0.39	-0.11	-0.05	0.26

	GP	NHLe PPG	PIMs/GP	Plus/minus	Shot blocking ability	Defensive awareness	Puck protection ability	Board battles	Work ethic & leadership
Backchecking ability	0.01	-0.01	-0.05	-0.01	0.12	0.11	0.08	0.09	0.01
Hockey sense	0.07	0.11	-0.08	0.04	-0.02	0.03	0.08	-0.07	0.03
Inconsistency in effort & performance	0.06	0.07	0.01	-0.01	-0.06	-0.13	0.03	-0.03	-0.17
Lack of physical strength	0.03	0.05	-0.19	0.05	-0.09	-0.03	-0.01	-0.02	-0.01
Passing & playmaking ability	-0.06	0.16	-0.15	0.03	-0.05	0.02	0.10	-0.06	-0.16
Shooting ability	0.00	0.16	0.10	0.06	-0.04	-0.03	-0.01	0.02	-0.01
Soft hands	-0.03	0.09	-0.13	0.03	-0.02	-0.08	-0.01	-0.06	-0.03
Willingness to fight	0.08	0.00	0.28	0.03	0.09	-0.08	-0.02	0.07	0.02
Work ethic & leadership	0.04	0.06	0.02	-0.04	0.00	0.05	-0.09	0.01	1.00
Board battles	-0.01	-0.06	0.08	-0.09	0.04	0.07	0.15	1.00	0.01
Puck protection ability	0.00	0.08	-0.12	0.03	0.07	0.10	1.00	0.15	-0.09
Defensive awareness	0.08	0.02	0.00	-0.02	0.26	1.00	0.10	0.07	0.05
Shot blocking ability	-0.01	-0.13	0.00	-0.06	1.00	0.26	0.07	0.04	0.00
Plus/minus	0.15	0.40	0.04	1.00	-0.06	-0.02	0.03	-0.09	-0.04
PIMs/GP	0.23	0.11	1.00	0.04	0.00	0.00	-0.12	0.08	0.02
NHLe PPG	0.45	1.00	0.11	0.40	-0.13	0.02	0.08	-0.06	0.06
GP	1.00	0.45	0.23	0.15	-0.01	0.08	0.00	-0.01	0.04
Age	0.03	0.16	0.03	0.04	-0.05	-0.08	-0.02	-0.07	0.00
Weight	-0.01	-0.08	0.31	-0.08	0.01	-0.01	0.14	0.22	0.00
Height	-0.14	-0.26	0.14	-0.16	0.02	-0.01	0.14	0.23	-0.08
CESCIN-adjusted CSB	-0.06	-0.05	0.03	-0.01	0.10	-0.01	-0.03	-0.03	0.02
Draft pick number	-0.09	-0.34	-0.10	-0.17	-0.01	-0.03	-0.10	-0.10	-0.01

	Willingness to fight	Soft hands	Shooting ability	Passing & playmaking ability	Lack of physical strength	Inconsistency in effort & performance
Backchecking ability	0.02	-0.06	-0.03	0.01	-0.04	-0.12
Hockey sense	-0.09	0.09	-0.03	0.14	0.11	-0.14
Inconsistency in effort &	-0.03	0.12	0.07	0.06	-0.05	1.00
Lack of physical strength	-0.06	0.08	-0.05	0.20	1.00	-0.05
Passing & playmaking	-0.15	0.17	0.01	1.00	0.20	0.06
Shooting ability	0.05	0.00	1.00	0.01	-0.05	0.07
Soft hands	-0.13	1.00	0.00	0.17	0.08	0.12
Willingness to fight	1.00	-0.13	0.05	-0.15	-0.06	-0.03
Work ethic & leadership	0.02	-0.03	-0.01	-0.16	-0.01	-0.17
Board battles	0.07	-0.06	0.02	-0.06	-0.02	-0.03
Puck protection ability	-0.02	-0.01	-0.01	0.10	-0.01	0.03
Defensive awareness	-0.08	-0.08	-0.03	0.02	-0.03	-0.13
Shot blocking ability	0.09	-0.02	-0.04	-0.05	-0.09	-0.06
Plus/minus	0.03	0.03	0.06	0.03	0.05	-0.01
PIMs/GP	0.28	-0.13	0.10	-0.15	-0.19	0.01
NHLe PPG	0.00	0.09	0.16	0.16	0.05	0.07
GP	0.08	-0.03	0.00	-0.06	0.03	0.06
Age	0.04	-0.03	-0.02	0.06	0.01	-0.05
Weight	0.16	-0.09	0.05	-0.20	-0.29	0.02
Height	0.10	-0.06	0.05	-0.18	-0.06	0.07
CESCIN-adjusted CSB	-0.04	-0.08	-0.07	-0.05	-0.02	-0.11
Draft pick number	-0.08	-0.10	-0.12	-0.16	-0.11	-0.08

Hockey sense	-0.07	0.04	-0.10	-0.12	0.02	0.07	0.11	-0.08	0.04	-0.02	0.03	0.08	-0.07	0.03	-0.09	0.09	-0.03	0.14	0.11	-0.14	1.00	-0.06
Backchecking ability	-0.04	0.01	-0.10	-0.01	-0.05	0.01	-0.01	-0.05	-0.01	0.12	0.11	0.08	0.09	0.01	0.02	-0.06	-0.03	0.01	-0.04	-0.12	-0.06	1.00

Table H2

Correlation coefficients between independent and dependent variables – defensemen sample

	Draft pick number	CESCIN-adjusted CSB	Height	Weight	Age	GP	NHLe PPG	PIMs/GP	Plus/minus	Shot blocking ability	Defensive awareness	Puck protection ability	Board battles	Work ethic & leadership	Willingness to fight	Soft hands	Shooting ability	Passing & playmaking	Lack of physical strength	Inconsistency in effort &	Hockey sense	Backchecking ability
Draft pick number	1.00	0.37	-0.22	-0.18	0.09	-0.09	-0.37	-0.12	-0.22	-0.08	-0.01	-0.06	-0.04	-0.12	-0.15	0.01	-0.05	-0.04	0.00	0.03	0.02	-0.03
CESCIN-adjusted CSB ranking	0.37	1.00	-0.02	0.02	0.09	0.02	-0.15	0.09	-0.04	0.00	-0.05	0.00	0.01	-0.01	0.01	-0.06	0.01	0.05	-0.03	0.08	-0.04	-0.02
Height	-0.22	-0.02	1.00	0.55	-0.04	-0.01	-0.25	0.21	-0.07	0.07	-0.09	-0.14	0.18	-0.04	0.09	-0.07	0.00	-0.14	-0.04	-0.11	-0.06	0.00
Weight	-0.18	0.02	0.55	1.00	0.02	0.08	-0.07	0.22	0.01	0.12	0.02	-0.01	0.19	0.08	0.07	0.01	0.16	-0.05	-0.35	-0.03	0.05	-0.05
Age	0.09	0.09	-0.04	0.02	1.00	0.01	0.09	0.02	0.05	0.12	-0.06	0.02	-0.02	0.12	-0.08	-0.04	0.08	0.06	-0.10	0.01	0.05	0.05
GP	-0.09	0.02	-0.01	0.08	0.01	1.00	0.35	0.10	0.13	0.11	-0.13	-0.07	-0.07	0.02	0.17	-0.04	0.05	-0.13	0.08	0.01	-0.02	0.05

	NHLe PPG	PIMs/GP	Plus/minus	Shot blocking ability	Defensive awareness	Puck protection ability	Board battles	Work ethic & leadership
Backchecking ability	0.00	0.00	0.00	-0.06	0.07	0.05	-0.02	-0.07
Hockey sense	0.10	-0.05	0.06	0.00	0.06	0.00	0.08	0.07
Inconsistency in effort &	0.05	-0.08	-0.03	-0.14	-0.05	0.05	-0.07	-0.08
Lack of physical strength	0.09	-0.04	-0.02	0.06	-0.05	-0.11	-0.12	0.00
Passing & playmaking	0.06	-0.04	-0.02	-0.05	0.11	0.17	0.06	0.18
Shooting ability	0.17	0.08	0.01	-0.04	0.07	0.04	0.06	0.03
Soft hands	-0.07	-0.12	-0.12	0.04	-0.01	0.04	-0.11	-0.05
Willingness to fight	0.03	0.27	0.05	-0.04	0.02	-0.03	-0.02	-0.03
Work ethic & leadership	0.18	0.05	-0.11	-0.04	0.08	0.17	0.10	1.00
Board battles	-0.05	0.14	-0.11	-0.02	0.10	0.00	1.00	0.10
Puck protection ability	-0.06	-0.14	0.00	0.04	0.01	1.00	0.00	0.17
Defensive awareness	-0.02	-0.06	0.07	0.06	1.00	0.01	0.10	0.08
Shot blocking ability	0.04	-0.06	0.00	1.00	0.06	0.04	-0.02	-0.04
Plus/minus	0.27	-0.02	1.00	0.00	0.07	0.00	-0.11	-0.11
PIMs/GP	0.01	1.00	-0.02	-0.06	-0.06	-0.14	0.14	0.05
NHLe PPG	1.00	0.01	0.27	0.04	-0.02	-0.06	-0.05	0.18
GP	0.35	0.10	0.13	0.11	-0.13	-0.07	-0.07	0.02
Age	0.09	0.02	0.05	0.12	-0.06	0.02	-0.02	0.12
Weight	-0.07	0.22	0.01	0.12	0.02	-0.01	0.19	0.08
Height	-0.25	0.21	-0.07	0.07	-0.09	-0.14	0.18	-0.04
CESCIN-adjusted CSB	-0.15	0.09	-0.04	0.00	-0.05	0.00	0.01	-0.01
Draft pick number	-0.37	-0.12	-0.22	-0.08	-0.01	-0.06	-0.04	-0.12

	Willingness to fight	Soft hands	Shooting ability	Passing & playmaking ability	Lack of physical strength	Inconsistency in effort & performance
Backchecking ability	-0.06	0.12	-0.03	-0.01	0.03	0.12
Hockey sense	-0.07	-0.03	-0.02	0.06	-0.08	-0.08
Inconsistency in effort &	-0.02	0.08	0.13	-0.04	0.03	1.00
Lack of physical strength	0.05	0.05	-0.14	0.02	1.00	0.03
Passing & playmaking	0.06	0.00	0.09	1.00	0.02	-0.04
Shooting ability	0.05	0.06	1.00	0.09	-0.14	0.13
Soft hands	0.01	1.00	0.06	0.00	0.05	0.08
Willingness to fight	1.00	0.01	0.05	0.06	0.05	-0.02
Work ethic & leadership	-0.03	-0.05	0.03	0.18	0.00	-0.08
Board battles	-0.02	-0.11	0.06	0.06	-0.12	-0.07
Puck protection ability	-0.03	0.04	0.04	0.17	-0.11	0.05
Defensive awareness	0.02	-0.01	0.07	0.11	-0.05	-0.05
Shot blocking ability	-0.04	0.04	-0.04	-0.05	0.06	-0.14
Plus/minus	0.05	-0.12	0.01	-0.02	-0.02	-0.03
PIMs/GP	0.27	-0.12	0.08	-0.04	-0.04	-0.08
NHLe PPG	0.03	-0.07	0.17	0.06	0.09	0.05
GP	0.17	-0.04	0.05	-0.13	0.08	0.01
Age	-0.08	-0.04	0.08	0.06	-0.10	0.01
Weight	0.07	0.01	0.16	-0.05	-0.35	-0.03
Height	0.09	-0.07	0.00	-0.14	-0.04	-0.11
CESCIN-adjusted CSB	0.01	-0.06	0.01	0.05	-0.03	0.08
Draft pick number	-0.15	0.01	-0.05	-0.04	0.00	0.03

Hockey sense	0.02	-0.04	-0.06	0.05	0.05	-0.02	0.10	-0.05	0.06	0.00	0.06	0.00	0.08	0.07	-0.07	-0.03	-0.02	0.06	-0.08	-0.08	1.00	-0.05
Backchecking ability	-0.03	-0.02	0.00	-0.05	0.05	0.05	0.00	0.00	0.00	-0.06	0.07	0.05	-0.02	-0.07	-0.06	0.12	-0.03	-0.01	0.03	0.12	-0.05	1.00