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DOES PULLING THE GOALIE  
LEAD TO A PLAYOFF APPEARANCE?

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LEAD TO A PLAYOFF APPEARANCE?

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## Abstract

The analytics movement took over the sports world in the last five to ten years. The movement originated in baseball and moved to football and basketball with great success. Hockey has yet to undergo an analytical decision-making boom like the other “Big Four” North American sports leagues. The closest decision within hockey that can be examined analytically is pulling the goalie late in games. Pulling the goalie is one of the most researched topics related to hockey. The results of this research have evolved since the 1980’s, but the focus has been on what is the best time to pull the goalie to maximize win percentage. There is little research on if the strategy is worthwhile in the long run. This study uses six years of historical game summary data from the National Hockey League to evaluate if the strategy can help teams improve their place in the standings and their likelihood to make the playoffs. A panel regression with team fixed effects was used to evaluate the effect of optimal pull percent on standing points; a logit panel regression was utilized to evaluate the likelihood to make the playoffs. This study found that the optimal pull percentage of a team is not significant in both models. The team quality effects of goals for average and goals against average were significant in the improving the number of standing points while only goals for average was significant in the likelihood of making the playoffs. What this means for the future is discussed within the discussion section of this study.

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## Chapter I: Introduction

The game is winding down. It has been a hard fought 56 minutes between in-state rivals the Oklahoma Sooners and the Oklahoma State Cowboys on the ice in the BOK Center in Tulsa. Despite jumping to a three-goal lead earlier in the third period, Oklahoma State leads by a score of four to three. With just over two minutes left and control of the puck, the Sooners opt to pull their goalie from his net; in doing so it allows them to have an extra forward or defenseman to play with. It creates an unmarked man for the defense to hopefully tie the game. Many puck battles and a couple faceoffs later...the goal horn blares. The Sooners tied the game at 4-4 as the final regulation horn sounds. The gamble paid off and both teams walked away with a point in the standings.

Pulling the goalie is a risky strategy. It creates a scenario that essentially says “next goal wins” between the two teams. In a final attempt to salvage a game with offense, one team risks leaving a largely uncontested net to score on. National Hockey League teams have done this for many years, and it can be found in other professional and recreational leagues as well. The National Hockey League credits New York Rangers coach Frank Boucher for the first goalie pull in either the 1939-1940 or the 1940-1941 season (Jones, 2022). The strategy stuck as the game adapted through different forms of goaltending, styles of play, and rule changes. Boucher started the trend by doing so with at most a minute left in the game; however, the conventional agreement is now that the best time to pull the goalie is with two minutes remaining (Jones, 2022). The time varies as teams hardly pull their goalie if they do not have possession of the puck. It would be ill advised to pull the goalie to the bench when a National Hockey League player is skating full speed ahead towards the net you are defending. That decision would be scrutinized for years to come and would baffle players and front office staff who are looking to



win games and trophies. The team pulls the goalie in a controlled environment and so they can start with all six skaters moving toward the net. This simple decision remains one of the most drastic decisions a coach can make in the waning moments of a game; therefore, it behooves teams to take an analytical approach to this decision.

While the analytical approach is necessary, the success rate for pulling the goalie is 15.4%. A successful goalie pull is where teams tie the game with the extra attacker, not that they successfully got their goalie to the bench. While this success rate is not amazing, it is still hard to score in the National Hockey League. While the odds are not great, that 15% likely will make a difference in the outcome. It made a difference to the Sooners in their game against the Cowboys. The impact of the successful outcomes outweighs the low success rate.

The analytics movement boomed in the 21st century. The first overt analytics strategies implemented by a North American professional team came from the 2002 Oakland Athletics. The Athletics play in one of the smallest markets in Major League Baseball; as a result, they have less money to spend on player salaries compared to large market teams like the New York Yankees. General manager Billy Beane created a strategy to build the best team with the limited payroll he had available. He focused on a new statistic built by analysts that he hired. This statistic rubbed his scouts the wrong way as he focused on On Base Percentage (OBP) above all else as he and his analysts felt it could lead to more runs and in turn more wins. This strategy ended up paying off for the 2001 Athletics as they made the playoffs on the lowest payroll in Major League Baseball. The story has been immortalized in Michael Lewis's book *Moneyball*. Since this point, many teams in Major League Baseball tried to adapt similar strategies including implementations for large market teams.

Soon after the book's publishing, more analytical approaches began popping up for other team sports. Basketball began taking more three-point shots after research showed that it was more effective than taking midrange jumpers on a per shot basis (Shea, n.d.). The Golden State Warriors became the poster child for this strategy with elite three-point shooters Steph Curry and Klay Thompson shooting at historic rates. They rode that strategy to four titles in an eight-year stretch. The National Basketball Association has witnessed new records for three-point attempts in games almost yearly and the midrange jumper is panned by those in league circles.

The National Football League struggled to get off the ground with its analytics movement; however, football is the most complex to quantify in terms of impact on a game due to the intricacy of the game of football. The biggest decision-making analytics opportunity was whether to go for it on fourth down or punt it away. Football teams are evidently very risk averse and would rarely go for it unless it was out of pure desperation. Teams focused on what could happen to their win percentage and how likely they would be to win if they go for it or settle for a kick. Teams started going for it more since 2015 which is roughly when this trend started taking over (The Next Gen Stats Analytics Team, 2021). Teams realized how beneficial it can be for their win percentage and started to adopt the strategy more. There are more complex factors in that modeling, but the consensus continues to be it is better to go for it if it is a toss up.

The National Hockey League's analytics movement has been much quieter. Prior analytical work has focused on the flow of the game and not decision making within the game (Vollman, 2016). The most well-known analytical work has been with Corsi statistics. Corsi is shot attempts for a team subtracted by the shot attempts against a team; however, the more impactful statistic is the Corsi percentage, which is one's own shot attempts divided by total shot attempts (own and opponent's) (Vollman, 2016). Corsi tells you which team controlled the pace

of play more effectively and likely who won the game. There always is variance, and a team with a higher Corsi could have lost the game due to the other team having a star goalie like Georges Vezina or Patrick Roy. Another public source for hockey data is Corey Sznajder on Twitter as @ShutdownLine. He posts about hockey microstats. Microstats focus on player impacts on the game. The types of microstats he publishes relate to successful zone entries, passes and shots at five on five (full strength), and other aspects of hockey that are not measured by official National Hockey League statistics. These microstats are great for a general manager making roster decisions but not any notable public work akin to the other big four North American sports.

Admittedly, hockey games are the hardest to influence with in game decisions as there are few dedicated stops and starts. Decision making in game often boils down to which line the coach decides to send out during the next shift. This type of decision making is all in service of winning the game; with the simplest decision to make of whether you pull your goalie or not. If you are up by a goal, obviously not. Keep him in there to preserve the lead and win those two points you desperately want! If you are losing, pull the goalie. It could work out where you force overtime and at least get one point.

Points are everything. Many times, one point is the difference between making the playoffs or going golfing. Coaches and players are most often win maximizers; and win maximizing comes with the desire to make the postseason. Forcing overtime creates the chance you can steal the game and both points in that overtime period or shootout if the score is tied at the end of overtime. The obvious downside is that if your opponent scores on your empty net, the game is “over” as you are down multiple goals with little time to go. The harsh risk reward proposition is perceived as a benefit to National Hockey League coaches. It needs its own analytical treatment to decide if it is worth it or not.

The easiest decision to look at analytically in the National Hockey League is pulling the goalie. The scenario happens in a relatively uniform scenario and there are instances nearly every night across the league where it happens. This study will focus on analyzing game summary data from past National Hockey League seasons to determine if pulling the goalie generates enough points to climb into the playoffs.

### **Purpose of the Study**

The purpose of this study is to determine if pulling the goalie in a one goal game can help a team over the course of the season actively climb into the playoffs with more added points.

### **Research Hypothesis**

**H0:** Pulling the goalie in a National Hockey League game does not impact the probability of getting a point from an overtime loss or a win, and therefore has no relationship with a team making the playoffs.

**H1:** Pulling the goalie in a National Hockey League game increases the probability of getting a point from an overtime loss or a win, and therefore improves the chances a team makes the playoffs.

### **Significance of the Study**

This study focuses on the impact of pulling the goalie for playoff standings. For National Hockey League teams, making the playoffs creates new chances at revenue with playoff games. For coaches and players, incentives and bonuses can be met by making the playoffs and continued success in the playoffs; not to mention a chance to add a championship to their resume. Players can increase their statistics on the season and leverage that for a pay raise when they enter free agency. Front offices, coaches, and players can all experience the hunt for a Stanley Cup by making the playoffs and have a chance to win it all. For the fans, more points can

lead to more playoff games and chances to experience playoff hockey. It also allows their team a chance to witness their team go on a championship run. Successfully pulling the goalie to score and force overtime also allows fans to experience the thrill of 3 on 3 overtime play, the current NHL overtime format. More overtime might encourage more fan engagement through future ticket purchases or merchandise sales. That money can then be poured back into the team or league and make the product on ice better. The stakeholders in this study could benefit from the results for improvements in the game of hockey. This study will be important as the game of hockey is lacking in other analytical decisions compared to the other “Big 4” sports leagues. Finding out if this strategy helps at all could impact teams for the better. If there is a null finding, coaches can try to win games in different ways that teams have not seen before.

### **Delimitations**

The dataset for this study will be comprised of game summary data for the five most recent National Hockey League regular seasons, including the shortened 2019-2020 and 2021 seasons. This dataset is enough to have a large sample size but still relevant to the current era of hockey being played. It is just regular season data due to the focus being on the regular season push to the playoffs. Teams pull their goalie in the playoffs too; however, the playoffs are almost an entirely separate season and must be treated as such.

### **Limitations**

The scenario of pulling the goalie is not specific to the National Hockey League as the rules in other hockey leagues are very similar to the National Hockey League. While this analysis will deal specifically with the National Hockey League and the data available on that league, the analysis could be adjusted to the specific lower-level leagues. The data will come

from National Hockey League players and their competitions against each other. Small adjustments could be made to generalize to other leagues with time and research.

### **Assumptions**

The biggest assumption of this study will be that all teams are trying to win and get points in every game they play. Front offices can create a roster that will try to lose on purpose, or “tank”, but the assumption is that coaches and players generally try to win across this dataset. Given that coaches are the individuals making these decisions, teams will be assumed to be win maximizers.

### **Operational Definitions**

*5 on 5*: normal state of National Hockey League play with each team has 5 skaters on the ice.

Can also be referred to as *5 v 5*.

*6 on 5*: when one team has their goalie pulled in favor of an extra skater on the ice. Also, can be referred to as *6 v 5*.

*Empty Net Goal*: team with their goalie in the net scored on the net of the opposing team that has no goalie.

*Goal*: When the puck crosses the goal line of the opposing team.

*Goalie*: Ice hockey player dedicated to stopping Shots on Goal and last line of defense against opposing team’s scoring chances. This player must stay in the net unless being pulled to the bench for an extra attacker. Also known as a *Netminder* or *Goaltender*.

*Skater*: Ice hockey player who plays the position forward or defenseman. These players can move all over the ice and a team is limited to five skaters on the ice at a time. Also, can be known as an *attacker* in pulled goalie situations.

*Overtime:* Period that takes place if game is tied after 60 minutes of regulation play. Teams play until time expires or a goal is scored. Regular season overtime is 3 on 3. Both teams receive a point for playing to overtime.

*Wild Card:* A playoff spot in each conference in the National Hockey League reserved for the two teams with the most points that did not finish top three in their division.

## Chapter II: Literature Review

Analytics is a fairly new term in the sports world, but there is some research to examine on this topic. The evolution of data availability, analytical thinking, and easier access to public discussion have made this a popular topic to write about. The field still does have some way to go to be like other fields of research. The strategy of pulling the goalie in hockey has been around for many years and is generally agreed upon to be a good thing within the game. The consensus is that it is worth it to try to win that game; however, there has not been a clear indication on if it can help a team make the playoffs. The in-game desire of being a win maximizer logically results in more wins which in turn should lead to more points. Do those points that are earned from trying to win maximize lead to a playoff appearance?

The following review includes many articles found by searching in Google Scholar with terms such as “pulling the goalie”, “hockey analytics”, and “hockey goalie”. During this research, roughly seventy-five articles were found and ten will be reviewed. Reasons for exclusion included overlapping research, general results, and lack of citations. Much of the research was found by following citations as well.

Some relevant books were encountered in a previous undergraduate course. These books are included as they cover the recent history of analytics and are important to the discussion of analytics in their respective fields.

The review of relevant sources will begin with papers and books on the general state of analytics in North American professional sports, will characterize the general data analytics approaches that have been taken in hockey, and will move towards the existing discussions on when to pull the goalie. Both sections are organized chronologically, as it shows the evolution of each topic of literature.



## Sports Analytics

One of the most notable books that pushed analytics to the forefront of the public sphere was *Moneyball* by Michael Lewis published in 2004. After starting a career working in and writing about finance and economics, Lewis spent time with Oakland Athletics' general manager Billy Beane during the 2002 Major League Baseball season as the A's put focus on OBP to scout players compared to previous metrics like batting average. Beane was a subscriber to an underground approach, known as sabermetrics, which he used to guide his decision making (Lewis, 2004). The decision to shift towards this lesser-known statistic was an approach taken because of the lack of money the Athletics could spend compared to big market teams (e.g. the New York Yankees) for the conventionally good players. To win the most games with their lower payroll, Beane used OBP to find players who were not as expensive and fit in their price range. The belief was that the players getting on base more will lead to more runs scored simply because they get on base. (Lewis, 2004). The result was a team that scored the most runs in Major League Baseball and made the playoffs with that low payroll. The A's focus on a new approach sent ripples through the baseball world. Success in sports often leads to new positions with other teams. Some of the front office staffers Beane brought in were then hired by other teams to replicate the same approach. The use of sabermetrics grew substantially after the 2002 season in baseball, but the book proliferated the discussion of analytics in everyday life for sports fans.

One of the next big analytical books took a broader approach and covered topics in many different sports. In 2011, Tobias Moskowitz and L. Jon Wetherheim published the book *Scorecasting* and it covered situations in football, basketball, baseball, and more. They also focused on the psychological aspects of thinking about sports and why teams are slowly

adjusting to these analytical decision-making processes. The authors also focus on situations that translate more to all sports than a specific one. Some of the problems come from generalizing them to certain sports. The authors pointed out that analytics are growing and there are some proponents of it, but coaches remain very risk averse. They credit several sources as helping grow the game; however, in the 12 years since this book's publishing teams are more willing to take these risks but there is still some risk aversion.

One topic covered in *Scorecasting*, going for it on fourth down in American football, became the starting point for American football discussions. One of the most recent publications was a master's thesis by University of Oklahoma student Erin Psajdl (2022). Due to the lack of other published sources, this thesis is considered due to it being an in depth look at one of the major analytical talking points as of writing this literature review. Psajdl looked at whether going for fourth downs that maximize expected win probability would increase wins in a season for a National Football League team (Psajdl, 2022). Unlike *Scorecasting*, Psajdl's analysis was long term for the entire season; *Scorecasting* just looked at probabilities within the game. Psajdl found that while maximizing expected win probability is not a clear way to win more games, teams did score more points and that it is a start to winning more games (Psajdl, 2022). Long term analysis of these analytical decisions is becoming more prominent and numerous in the field of analytics. There remains work like this to be done in the hockey world but there have been some smaller revelations and studies done for hockey analytics.

### **Hockey Gameplay**

Before we discuss hockey analytics and field specific research, the basics of hockey game play should be established. Hockey is the least popular of the big four North American sports leagues; therefore, it is understandable that there is some unfamiliarity with the game. At its most

basic, the objective of the game is to score more goals than the opponent by striking a flat cylindrical puck into an opponent's goal (net). Regarding player positions, a team typically has three forwards, two defenseman, and one goalie on the ice to accomplish that objective; this is referred to as five on five (even strength). Five refers to the number of skaters who can go all over the ice rink. The goalie typically stays in and around the goal and is not counted for strength codes. If a team takes a penalty, the player who committed the penalty is sent to the penalty box and results in a power play for the opponent; the strength code is therefore five on four. Forwards are usually moving towards the net and scoring goals. Defensemen usually stay back in the defensive zone and are responsible for clearing the puck out of the area of their own goal. Goalies stop the puck from going in the net and are the last line of defense for the team.

The ice is divided into three zones. The offensive zone is when Team A controls the puck and is shooting at the goal where they can score, i.e. Team B's goal. The neutral zone is between the offensive zone and defensive zone in the middle of the ice. It is the transition part of the ice that the team benches are situated, and the puck can go to either zone quickly. The defensive zone is when Team A is defending their net from being scored on. The forwards and defenseman can rotate across these zones as the movement of play (the puck) dictates.

The game is played in three twenty-minute periods. If the game is tied in the regular season, teams play one five-minute overtime period of three on three "sudden death"; i.e. the next goal scored wins the game in overtime. If the score remains tied at the conclusion of overtime in the regular season, the teams participate in the shootout to determine the winner. A win is worth two points in the standings while a regulation loss is worth zero points; however, an overtime loss is worth one point. The standings are determined by how many points teams have. The top three teams in each division make the playoffs and then two wild cards.

If a game is tied in the waning minutes of the third period, a team may pull their goalie for an extra skater. The downside to this strategy is that the opponent can shoot the puck in their unguarded net to essentially ice the game. The strategy is a last-ditch effort to try to win the game and earn the points for the standings. The empty net is one of the most common strategies employed by all teams and is seen as a benefit. Forwards are tasked with scoring more goals and having an unguarded player on the ice can create much needed pressure on the opposition.

### **Hockey Analytics**

One of the first studies done on analytics and predictions was published in 2011 by Samuel Buttrey, Alan Washburn, and Lewis Price; the researchers wanted to determine if dynamic programming was a viable technique to predict scoring rates for teams. This research treated goals as Poisson events and would happen at random times. The analysis was performed using web scraped data from the 2008-2009 National Hockey League season (Buttrey, Washburn, & Price, 2011). After determining the length between goals for and against for the 30 teams, the model created a ranking for teams to predict what the score and outcome of individual games would be. This model was accurate in predicting outcomes and defensive metrics; however, the model was a statistically significant improvement over real scoring outcomes. The dynamic programming method was used by Washburn in a 1991 study that will be covered later in this paper. This predictive research shows there is a use for analytical models and data for hockey to use. The lack of statistical significance holds this research back from being super applicable to the current field; however, it does show there are good predictive models to use.

Ranking players is another common application of hockey analytics. Brian MacDonald, Craig Lennon, and Rodney Sturdivant (2012) created a ranking of players based on shot location and number of shots taken. After scraping three seasons worth of game summary data, the

researchers ran logistic models with predictors like shot angle, location, angle change (for if a shot is a rebound or not), and more (MacDonald, Lennon, & Sturdivant, 2012). This logistic model would calculate the total goals a player scored. The data also included the players on ice for goals; the goals scored against a player's team are counted as a negative. From there, a plus/minus type system was created to rank players from what the model predicted they would produce. The more goals a player scores while giving up fewer goals, the better. Much of the research is skewed towards the star players of the league and forwards in my opinion.

Defensemen often do not score as many goals to outweigh their goals against. The ranking system is not much different than a plus/minus of actual goals. While this model does try to be predictive, I believe this research is best used to compare the performance of players rather than rank them.

Another group of researchers published a new attempt at a shot chart. Shot charts visualize where teams are taking shots and would work well with the research of MacDonald et. al. Hannah Pileggi, Charles Stopler, J. Michael Boyle, and John T. Stasko (2012) created the visualization tool SnapShot for the Institute of Electrical and Electronics Engineers visualization conference in 2012. SnapShot improves upon the traditional shot chart of glyphs and dots representing shots and creates a radial heat map of shots by teams throughout an entire season. Many shot charts, then and now, only focus on displaying the location and result of the shot. SnapShot allows for a clearer picture of a team's offensive identity (Pileggi, Stropler, Boyle, & Stasko, 2012). This visualization tool allows for coaches and general managers to make roster or strategy changes. The information present is easy to understand but can oftentimes be harder to change in practice. The analytical insights are not like the decision making of the other big four sports and shows why there is a need for these kinds of tools and research in the sport.

In 2016, Rob Vollman wrote the book *Stat Shot* and it covered the wide variety of hockey analytics that analysts had worked on. The grouping shows how lacking analytics are in hockey compared to the other professional sports. The stats in this book are about puck possession, goalie stats, and roster construction (Vollman, 2016). Much of the focus is on evaluating players. The book can be for general managers, but coaches are still an important part of the hockey community. The book hints at other statistics but never delves into them or their validity in hockey. The problem with this book compared to other sports analytics research is there is not a full discussion on any in game decision making akin to going for it on fourth down or on base percentage with *Moneyball*.

In 2017, the new PageRank (PPR) system was tested on its capabilities to predict playoff series. Using a team's Corsi rating and PPR models, Nathan Swanson, Donald Koban, and Patrick Brundage tested how accurate the model could predict the outcomes of playoff series from the 2008-2016 National Hockey League seasons. The inclusion of Corsi in the PPR system tests how impactful and predictive the major analytical stat in hockey is. After training the PPR model with data, the model correctly predicted the outcome of a playoff series 70% of the time (Swanson, Koban, & Brundage, 2017). Much of the predictive work in this research was done to evaluate if the machine learning style of PPR applies to hockey. The successful accuracy of the model indicates there is a place for machine learning; however, the PPR model here does not help fill the gap in game decision making analytical tools. Predictive works are good for general managers and their usage is important to the advancement of the analytical tools within hockey.

Namita Nandakumar and Shane Jensen (2019) then summarized the analytical workings of the hockey world from beginning of the stat sheet to the trends that are still present today. Much of hockey's current analytics are related to shot measurements. The biggest one is touched

on here yet again, Corsi. Corsi was the first major in game analytic that teams used to look at who controlled the pace of play more meaningfully. After Corsi came about and shots became the focus of analysts and teams, the community moved to evaluating the quality of those shots and how those shots could lead to expected goals (Nandakumar and Jensen, 2019). This analysis is still just about game strategy and not in game decision making which is the big thing lacking in hockey analytics compared to other sports. The next step came in the form of measuring goalies and their save percentage on these expected goals; this was a logical step since many consider goalie to be the most important player on a hockey team (Nandakumar and Jensen, 2019). The next phase of analytics focused on player aging regarding contracts and when to draft certain positions. There is no focus on a singular in game decision that can be compared to the other professional sports. Hockey remains behind the other North American professional sports regarding analytics; however, there is one subject that has been analyzed for a long time in the hockey world.

### **When Should You Pull the Goalie?**

Much of the existing literature related to goalie pulls focuses on when a team should pull their goalie. The literature's primary focus is on whatever the optimal time to pull the goalie is during a game. This topic is by far the most common hockey analytics topic.

The first major paper published on the topic of pulling the goalie was done by Donald Morrison and Rita Wheat in 1986. This paper was correcting a previous paper published by Morrison using new information from the National Hockey League. Morrison also acknowledges that his initial paper was not very good as his data was estimated and was not accurate to what really happened in games (Morrison and Wheat, 1986). The study was performed with the same analysis and Poisson distributions as the original paper in 1976; however, Morrison considers

this work much better as he was provided game summary data from the National Hockey League itself (Morrison and Wheat, 1986). The data was much cleaner and easier to calculate the correct probabilities for the Poisson distribution. With more accurate probabilities, Morrison ran his analysis again with 387 observations of when the goalie was pulled in the 1979-1980 National Hockey League regular season (Morrison and Wheat, 1986). The probability of scoring a goal was calculated at different time frames and events. When the probability of obtaining a tie and getting a point was greater than the probability for losing and getting no points, that was the optimal time to pull the goalie. Morrison and Wheat found this time to be with 2:34 left to go (1986). This research is obviously very old and might not apply to today's National Hockey League; however, much of the peer reviewed research stems from this model and approach to the topic. The original research was corrected and gave way to other articles that focused on the same topic.

Five years after Morrison, Alan Washburn published his own research on pulling the goalie; however, he used dynamic programming to factor in game states to see if that produced a different time than Morrison's previous research (1991). Washburn focused on a more comprehensive probability function to see if it could create an agreement between the time coaches pulled and what the optimal time Morrison published. Washburn used the same dataset as Morrison to conduct his analysis: game summary data provided by a National Hockey League employee. Using his new model, Washburn found more extreme pull times than what Morrison had found by nearly 30 seconds (1991). Washburn was surprised by this but also noted his model is based on the highest probability of winning and not just probability of a tie. It should be noted that the shootout did not exist in the National Hockey League until the 2005-2006 season; shootouts take place after overtime and eliminated ties. Both teams still get a point for going to a



shootout, so it is like a tie for analysis purposes. Washburn understands pulling the goalie with nearly three minutes left in the game could be considered extreme and does not agree with conventional wisdom at the time (1991). Since these two initial studies, teams have started pulling their goalie earlier; however, teams have not been pulling their goalies at these times. It still inspired more research from others.

The next big paper was by David Beaudoin and Tim Swartz in 2010. Their focus was on when to pull the goalie depending on what type of situations a team was in; these situations included 5v4, 4v5, 5v3, and more (Beaudoin and Swartz, 2010). This research was the next big step in creating a comprehensive guide for pulling the goalie to coaches. The purpose of this article was to create a table of scenarios and when to pull the goalie in those scenarios for future stakeholders. Coaches, players, general managers, and owners could benefit from this as the stakeholders and is who the article is written for. Unlike Morrison and Washburn, their data was obtained by scraping game summary data from nhl.com for the 2007-2008 season (Beaudoin and Swartz, 2010). Their analysis differed from others by simulating games with exponential distributions derived from previous research and including Bayesian parameter estimates to simulate in game events; the simulation was given events the researchers were interested in and when that happened, the goalie was pulled. After that, the average number of points that teams received from pulling the goalies was compared to the games where the goalie was not pulled (Beaudoin and Swartz, 2010). The simulation was run for different scenarios and the scenario with the highest average number of points had a time associated with it. After that time, the situation with the highest average number of points is the condition on which teams should be pulling their goalie. The researchers focused on four different situations, but these yielded the same results: teams should be way more aggressive as it leads to more points in the long run

(Beaudoin and Swartz, 2010). The research still focused on when to pull the goalie but addressed a gap in the literature. Their call for a more aggressive strategy has been heeded by teams since then; however, they are still not near as aggressive as the researchers suggested. A simple situation chart the authors created demonstrating when to pull the goalie is useful but lacks what the optimal strategy should be at that time. It would allow coaches to see how much more aggressive they should be.

The next big change in the research would be breaking the game down into ten second segments and evaluating these segments individually. Clifford Asness and Aaron Brown published an article in 2018 that focused on that same aspect. Their data was obtained from the National Hockey League website, and they pulled the total number of goals scored in the 2015-2016 regular season. After obtaining the goal numbers, they divided that number by even strength minutes played to get how many goals were scored per minute; this probability was then divided by six to split the game into ten second increments and find a probability of scoring in those ten seconds (Asness and Brown, 2018). They repeated the process with even strength goalie pull minutes to find the probability of scoring in a ten second interval. The percentages found were then used to create probability functions that time could be fed into to give expected points for situations. The point where expected points with an empty net are greater than expected points with a goalie in net is the optimal time to pull the goalie. The functions were adjusted for how many goals a team is down by and it yields very aggressive times (Asness and Brown, 2018). The researchers recommend pulling the goalie in the second period if you are down by three goals! The researchers created one of the most accurate models from a game time perspective. The research still just focuses on when to pull the goalie and not if it leads to anything in the long run.

Only one year after Asness and Brown's article, Zia Zaman and Hong Ming Tan took the previous researchers' work one step further: they accounted for what zone the puck was in (2019). Zaman and Tan focused on improving the Asness and Brown model to see if puck location was important enough to change when teams should pull the goalie. Using all the same parameters and data as Asness and Brown, these researchers changed some of the probabilities to account for the puck being in one of the three zones at the start of that 10 second interval; then the researchers used the same formulas as Asness and Brown (Zaman and Tan, 2019). The findings were very similar to the previous research. One of the best things about this article is there is a table that can be shown to teams as a simple chart for where the game is at certain times. This research is easy to show to stakeholders and incorporates new ideas into an old topic for analytical readers.

### **Summary**

Sports analytics have come a long way in the time for the public eye and the topics discussed have grown a lot. Ever since *Moneyball*, analytical writing has become more popular and prevalent. Writings have been focused on broad topics in certain situations. There is a lack of research on which strategies are good for full seasons or if these strategies are worth it in the long run. The general writings on the topic are just summarizing what the analytical decisions are. There are more writings in hockey specifically about pulling the goalie; however, their primary focus is on when to pull the goalie. There is a gap in the literature about whether teams should continue to pull the goalie. The strategy has been around for so long that it is tradition. With the more aggressive approaches published by recent researchers, a fair question to ask would be if the aggression is worth it.

### Chapter III: Methods

The decision to pull the goalie can happen in any National Hockey League game. This strategy has been studied numerous times through the lens of when to pull the goalie. There is a lack of research on if pulling the goalie works in the long term. The purpose of this study is to determine if pulling the goalie leads to any long-term benefits in the form of a playoff appearance. The first steps would be to determine how many additional points had been earned in a season from scoring with the goalie. The next step would be to repeat the process for multiple seasons. A more robust analysis is needed to evaluate this decision compared to if and when teams should pull the goalie. The study can incorporate what the playoff cutoff would be as the lowest number of points that made the playoffs, regardless of conference. There can be differences between the playoff line for the eastern and western conferences each season; however, the strategy is employed in both conferences and as such should be evaluated for the entire league. The research hypothesis for this study is that pulling the goalie does lead to more points in a season which can lead to a playoff berth or better playoff seeding. To accomplish this, this study created a regression model to predict how many points a team can expect to earn from pulling their goalie during a season.

This chapter will discuss the methods used to build this comprehensive regression analysis to evaluate the points earned in a season. This model incorporated elements and analysis from previous research to analyze the validity of this strategy. This research is historical and applied research as it attempts to find a practical answer and bring a new perspective to a long-standing coaching strategy. It is non-experimental research since it simply observes and analyzes a data set and there is no intervention done on a variable. It also attempts to describe the benefits of pulling a goalie; therefore, it has a descriptive element to it. There is also a correlational

element to the research. The research focuses on if there is a correlation between the success of pulling the goalie in getting to overtime and playoff appearances. Like with other analytical decisions in sports, we will not know what happened if the teams did not pull the goalie and if the result was different with that different strategy. The purpose, again, is to evaluate if this strategy is a worthwhile strategy to win maximize for coaches and a playoff berth.

### **Sample**

Due to the historical nature of this study, a recruited sample is not needed. The data was collected from the hockeyR package. R is an open-source coding platform that has packages for a wide variety of fields that offers great data analysis and visualization options. R code is reproducible for future research and can easily be modified. Packages like hockeyR are updated regularly by their managers and creators. R is also the most commonly used software/coding language among sports analysts.

The data of interest from the hockeyR package is the game summary data. This set of data is the play-by-play descriptions of events in actual National Hockey League games going back to the 2010-2011 season as that is as far back as the JSON scraper will go (Morse, 2023). This game summary data includes events that happened on the ice like if it was a shot on goal, if there was an empty net on the play, and more. The raw data can be filtered down to all the plays recorded that have an empty net to create a sample that is specific to the empty nets. This sample is similar to the studies done by Morrison & Wheat (1986), Washburn (1991), Asness & Brown (2018), and Zaman & Tan (2019). All those previous studies used game summary data and filtered down to empty net plays and goals; the main difference between this literature and the current research is the focus is on long term benefits rather than when to pull the goalie in a specific game.

## Data

The tables below categorize the variables in the dataset from the hockeyR package. The variables are the different events tracked by the National Hockey League and how they were recorded. Not all variables will be included as they are not important to the analysis of pulling the goalie.

**Table 1**

*Variables Obtained from game summary data in hockeyR package.*

<b>Variable</b>	<b>Description</b>
event_team_abbr	Team abbreviation that caused event to happen
game_seconds_remaining	How many seconds remain in the game
home_score	Score of the home team
away_score	Score of the away team
strength_state	Which state the game is in for skaters (e.g. 4v5)
gd	Goal differential at time of event (derived from home_score and away_score)
gf	Goals scored by a team
ga	Goals allowed by a team
gfa	Goals scored by a team per game for a season
gaa	Goals allowed by a team per game for a season
st_points	Standing points accumulated by a team. Used to determine who makes the playoffs
playoffs	Binary variable indicating which teams made the playoffs or did not

## Research Design

The research will be conducted in the following steps. The details of the steps will be discussed further in a future section.

1. *Define what would be classified as an optimal strategy.* This identifies exactly what to look for within the data and builds upon previous research to decide what is the optimal strategy.
2. *Create a panel regression with team fixed effects model to calculate expected points added for optimal pull percentage.* This model will be used to estimate how the points added could be in a season. It also allows for future research and reevaluation.
3. *Create a logit panel regression with team fixed effects model to calculate likelihood to make playoffs based on optimal pull percentage.* This will determine if pulling the goalie leads to increased chances of making the playoffs.
4. *Evaluate the model fits and determine if pulling the goalie is a beneficial strategy.* This will determine the success or failure of the strategy.

### **Threats to Validity**

Since the data is all historical data from entire National Hockey League seasons, there are little internal threats to validity. The biggest threat to internal validity is the lack of a uniform strategy or pull time. The variance in when teams pull the goalie can result in inconsistent outcomes and not give a well-rounded picture for the strategy. The inconsistency of the strategy could skew results and not create an accurate picture of what the strategy could lead to. The biggest threat to validity is generalizability; this threat is due to the change in team complexion every year. Players change teams through trades or free agency which changes how teams can compete each year. Changes in strategy from year to year, from roster talent or a new philosophy, could skew the data and possibly change how the data reacts to that. Any model or results would have to be adjusted as changes occur or the essentially random fluctuations may be accepted as mean zero “noise”.

## Data Management and Analysis

The data and analysis will all take place within the R Studio and R related software. The study will include descriptive and analytical components. Descriptive statistics will be presented in table and graphical form to outline how trends and the models presented.

The data analysis process will include the previously mentioned steps: 1) define what would be classified as an optimal strategy, 2) create a panel regression with team fixed effects to calculate the expected points added from optimal pull percentage, 3) create a logit panel regression with team fixed effects model to calculate likelihood to make playoffs based on optimal pull percentage, 4) evaluate the model fits and determine if pulling the goalie is a beneficial strategy.

1. *Define what would be classified as an optimal strategy.* This step is used to filter down games to match what would be identified as the optimal strategy. The optimal strategy has often been found in research to be between two and three minutes remaining in one goal games. As a middle ground, the optimal time should be set at two and a half (2:30) minutes remaining in the game. Another assumption to be classified as optimal strategy is that this strategy is deployed within one goal games. The numbers and style of play changes when you are down multiple goals that this strategy might not be applicable. The focus of this study is on the close games and their results. Multiple goal games are often less common for teams that would benefit from this analysis and will be excluded from this study.
2. *Create a panel regression with team fixed effects model to calculate expected points added for pulling the goalie.* Building this model will incorporate the seasons that have been analyzed. This model could be used for each new season, with tweaks, to give a



baseline for how effective the strategy could be that season. The model will be a panel regression with team fixed effects of points added in each season. This model will consider relationships of past seasons data to possibly estimate how many points a team can expect to earn in a following season. This model's predictive power could be useful to coaches in evaluating the strategy in context of each season as the next step demonstrates. Another model could be used to predict minimum number of points needed to make the playoffs. A comparison between the two models could be done as another point of evaluation.

3. *Create a logit panel regression with team fixed effects model to calculate likelihood to make playoffs based on optimal pull percentage.* This logit panel regression will determine the additional likelihood to make the playoffs by a change in optimal pull percentage. This model's predictive power will be similar to the panel regression for expected points added. This model will also consider the past seasons and the changes between the seasons.
4. *Evaluate the model fits and determine if pulling the goalie is a beneficial strategy.* Once the models are run, the evaluation of their results will determine the usefulness of this strategy. The models will determine which factors are statistically significant and impact the number of points and likelihood to make the playoffs.

## **Model**

Due to the time-invariant characteristics of teams over the seasons sampled, and to avoid violating the OLS regression assumption of independence of observations, team fixed-effects panel regressions will be used. Panel regression was chosen as that will account for the repeated

observations of teams. The time-based aspects of this research dictate the need for this type of model. The model is formatted below,

$$EPA_{it} = \beta_0 + \beta_1 OPP_{it} + \beta_2 GFA_{it} + \beta_3 GAA_{it} + \alpha_{it} + u_{it}$$

where EPA is expected standing points added in the season t for team i,  $PPG_{it}$  is the ratio of the times a team pulled their goalie at the optimal time within season t for team i,  $ATPG_{it}$  is the actual amount of times they pulled the goalie at the optimal time within season t for team i,  $GF_{it}$  is the goals scored for a team i in season t, and  $GA_{it}$  is the goals scored against team i in season t,  $\alpha_{it}$  is the entity-fixed effects term, and  $u$  is the error term.  $GF_{it}$  and  $GA_{it}$  are included to account for overall offensive and defensive quality respectively to control for the differences between a team during the different seasons. A similar fixed effects logit panel regression will also be used to examine the impact of the strategy on playoff qualifications. In this case the dependent variable will be a binary “made playoffs” indicator,

$$LPQA_{it} = \beta_0 + \beta_1 OPP_{it} + \beta_2 GFA_{it} + \beta_3 GAA_{it} + \alpha_{it} + u_{it}$$

Panel regression was chosen as it accounts for the team fixed effects over multiple points in time for the different seasons. One of the assumptions that must be met includes the independence of errors from other entities that are being measured in that model. The error terms for that model will only be associated with one team at one time. The model must also have homoscedasticity and the entity-fixed effects cannot be correlated with the independent variable of how often they pulled the goalie optimally. The same fixed effects assumptions are present for the logit model. The relationship between the independent and dependent variables for both models is assumed to be linear.

These models will be created using the fixest R package and evaluated by testing for statistical fit (Berge, 2018). If the model is a good fit, the beta coefficients will be tested against a null hypothesis set to equal zero. A statistical significance for the panel regression would

indicate that these expected points added would benefit teams in making the playoffs. For the logit model, a statistical significance would note how much more likely a team would be to make the playoffs and which factors are significant in improving or decreasing the chances to do so.

## Chapter IV: Results

This chapter focuses on the presentation of the findings of the research. It will be organized chronologically based on how the study progressed. This includes descriptive statistics and model interpretations.

### Data Organization

The first step in the research was to gather all the data for the previous six completed seasons using different filters and manipulation. This started by gathering play by play data for the season and selecting the first time in a game where the goalie was pulled in the last three minutes of a game. From that filtering the data was tested against the optimal criteria for a goalie pull. The optimal criteria decided upon would be if the goalie was pulled with 180 game seconds remaining in a game with a goal differential of one where the strength state was six on five (6v5). Columns were added to include the number of optimal pulls and non optimal pulls. Next, the number of standing points teams accumulated by teams was gathered using a function in the hockeyR package. Due to different scraping sources, an extra step was needed to address the different abbreviations used to refer to the Vegas Golden Knights. Next the goals scored for, and goals scored against for a team in a season were calculated. A binary variable was coded for teams that played more than 82 games in the season. Playing more than 82 games means that a team qualified for the playoffs and was represented by a value of one (1). Once these columns and data frames were collected, they were joined together to create the final data frame necessary for analysis. Using the final data frame, the optimal pull percent, goals for average, and goals against average were calculated. This process was repeated across all seasons; the final data frames were collected into a new data frame for all years within the study.

## Descriptive Statistics

Using the ‘all years’ data frame, different summary statistics were calculated and can be seen in table 2. There were 188 observations of all variables that were included in the final analysis. The number comes from the National Hockey League having thirty-one teams for four of the years in this time frame and expanding to thirty-two teams in the last two years of the study. Due to the shortened 2019-2020 and 2020-2021, goals for and goals against average were used due to the different number of games within the season. There is little variance within the goals for and goals against average as well as the optimal pull percent. Standing points has a wider variance as can be seen with the disparity between the min and max values. Teams also appear to pull optimally than non optimally.

**Table 2**

### *Descriptive Statistics*

Variable	N	Mean	Std. Dev.	Min	Max
gfa	188	3.007	0.366	2.000	4.110
gaa	188	3.233	0.302	2.444	4.198
optimal_pulls	188	10.79	3.520	3	22
non_optimal_pulls	188	9.835	3.560	2	20
optimalPullPercent	188	0.525	0.124	0.188	0.846
st_points	188	84.22	19.107	37	135
playoffs	188	0.505		0	1

*Gfa, gaa, optimal\_pulls, non\_optimal\_pulls, st\_points are count observations,*

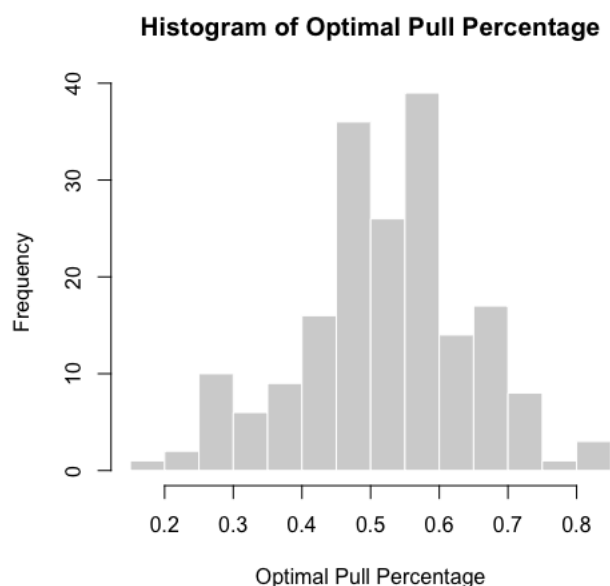
*optimalPullPercent is a percentage, playoffs binary variable.*

The normality of optimal pull percent was also examined. Figure 1 displays the histogram. This histogram shows there is a slight skew to the left, but the distribution of optimal

pull percent does appear to be normally distributed based on the ensuing histogram. A Kolmogorov-Smirnov test returned a p-value of 0.023. This result is less than 0.05 which means optimal pull percentage is not normally distributed. The mean optimal pull percent being slightly above 0.5 supports this skew as well. The skew also indicates most teams are pulling their goalies optimally more times than they are not.

### Figure 1

*Histogram of Optimal Pull Percentage*

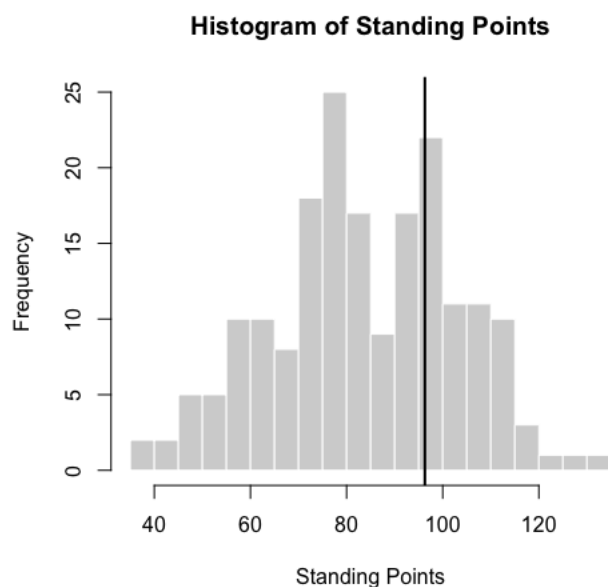


Another histogram was constructed to look at standing points. This histogram is shown in Figure 2. This histogram indicates wider variance as there are lots of different numbers of points a team can earn ranging from 0 to 164. A Kolmogorov-Smirnov test returned a p-value of 0.573 meaning that standing points is normally distributed. The black line on the histogram indicates the mean number of points needed to qualify for the playoffs across the six seasons of analysis; that average was 96.284. The additional line matches up with the second highest frequency of standing points acquired. Figure 2 is normally distributed and shows the different classes of

teams that are in the National Hockey League. Some are well to the right the playoff line while some are fighting close to the playoff line to get above it.

## Figure 2

*Histogram of Standing Points*



## Model Fit

Upon completion of descriptive statistics, the panel with team fixed effects and logit panel regressions were run and these are stated in Table 3 below. The panel regression with team fixed effects returned an R2 of 0.656 and adjusted R2 of 0.580. For the logit panel regression, the R2 is 0.466 and the adjusted pseudo R2 is 0.218. The log likelihood is -73.4 and the Bayesian Information Criterion (BIC) for this regression is 330.1. The BIC for the panel with team fixed effects model is 1624.3.

**Table 3***Model Fit Statistics*

	Panel with Team Fixed Effects	Logit Panel
R2	0.656	0.466
R2 Adj.	0.580	0.218
R2 Within	0.470	0.242
R2 Within Adj.	0.460	0.211
AIC	1511.0	216.8
BIC	1624.3	330.1
RMSE	11.17	0.36
Log Likelihood		-73.4

**Regression Results**

Along with the model fit statistics, results were returned to show what the significant factors were, and coefficients are displayed in Table 4.

For the panel regression with team fixed effects, the estimate for optimalPullPercent p-value is 0.946 and is not statistically significant on the expected points added. The goals for average and goals against average had estimates of 39.616 and 14.387, respectively. For each increase in goals for average, the expected points added goes up by 39.616; for every increase or decrease in goals against average, the expected points added decreases by 14.387. The p values are both less than 0.001; both factors are statistically significant in predicating expected points added. The standard errors for the variables are 7.4891 for optimal pull percent, 2.75355 for goals for average, and 3.72669 for goals against average.



The logit panel regression returned similar results. `OptimalPullPercent` is not a statistically significant result with a p-value of 0.511. Goals for average produced log odds of 2.061 with a p-value of less than 0.001. For every one goal increase in goals for average, a team's odds of making the playoffs increases by roughly a twofold factor. With a p-value less than 0.001, goals for average is statistically significant in impacting playoff qualification for a team. Goals against average returns a p-value of 0.494 and is not statistically significant.

Due to the lack of statistical significance of `optimalPullPercent` factor, the null hypothesis cannot be rejected. This conclusion means that pulling the goalie does not lead to more expected points from overtime and would then has no relationship to making the playoffs. This conclusion and decision will be discussed further in the next chapter.

**Table 4**

*Regression Results*

Variable	Panel with Team FE			Logit Panel		
	$\beta$ Estimate	SE	P-Value	Odds Ratio	SE	P-Value
<code>optimalPullPercent</code>	0.512	7.489	0.946	1.164	0.228	0.511
<code>gfa</code>	39.616***	2.754	<0.001	2.061***	0.113	<0.001
<code>gaa</code>	14.387***	3.727	<0.001	0.917	0.125	0.494

+  $p < 0.1$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

## Chapter V: Discussion

The first major finding within the research was that the optimal pull percent is not statistically significant in both models. While much of the research discussed in the literature focused on the optimal time to pull the goalie, the assumption in that research was that it does help teams over the course of the season. The researchers often discussed how pulling the goalie could lead to more wins which could lead to more playoff appearances; however, this research indicates that pulling the goalie at an optimal time does not affect a team's chances of getting more points or making the playoffs. This finding indicates that teams should change their strategy in the late stages of a game. The current strategy has no statistical impact on the team's performance. One practical application could be to develop a new strategy for late game situations where teams were normally pulling the goalie. With the assumption that coaches are win maximizers in game, the current strategy does not produce significant results to aid in win maximizing. The benefits gained are marginal and not a drastic improvement or hinderance to the goal of winning all the games they can. While pulling the goalie is a desperation move, the ultimate risk and reward tradeoff does not have results to show its continued usefulness.

The goals for average (GFA) variable was statistically significant in both models. This makes sense within the context of hockey; the team that wins is the one that scores more goals. The high coefficient seems to be a weird number though. That coefficient is very high for standing points; however, there is such a wide range of points available it can make some sense. It is interesting to see that one change in goals per game resulted in such drastic shifts in the standings per team. One additional goal could swing many games in different directions and improve the standings. This finding does line up with previous research as oftentimes more goals on a team leads to more wins. Teams often search to add goal scorers who fit their salary cap at

the time and its benefits on their team talent level (Vollman, 2016). Teams are always looking to increase their offensive output as it is often the easiest issue to identify and fix. This finding is in line with general practices already and can help teams both make the playoffs and increase the standing points they acquire during the regular season.

On the other side, goals against average (GAA) was only statistically significant in the panel regression with team fixed effects. The coefficient here does seem to be confusing. For every additional goal against per game given up, you gain roughly fourteen standing points. While you want to score additional goals per game, giving up more goals per game can be riskier as you might not be able to match the goal you give up. This coefficient is not as impactful on expected points added as goals for average. Defense is often less impactful on standings due to the recent trends of higher scoring games within the National Hockey League. Even with those current trends, it does seem to go against conventional wisdom within the sport. Teams and decision makers would think that a lower GAA would lead to higher standing points. This coefficient is odd and while it is significant, there are some questions for if it is correct or measuring this correctly.

The panel regression with team fixed effects is a decent fit for the data. The R2 for that model is 0.656 with an adjusted R2 of 0.580. The adjusted R2 indicates that 58% of the variance is explained by the independent variable when adjusted for the number of predictors. That indicates that most of the variance can be explained by the three predictors within the model. The fit could be better but does explain much of the variance within the model. This fit statistic could be improved with more factors and predictors but it does a good job with the data that it was given. This model is pretty good for predicting the expected points added but does not fully explain the relationship between these variables.

The logit panel regression was not as good of a fit. The BIC is 330.1 and log likelihood of -73.4. The BIC is a model fit measure for logistic regressions that penalizes model complexity in hopes of balancing goodness of fit and model simplicity; lower BIC values indicate better model fit. The lower BIC value of the logit panel indicates this model is a good fit for the data as it fits the general trend for BIC values. Log likelihood is a metric of fit where the further away from zero, the better the fit. The value of -73.4 is a good bit away from zero and indicate this model would be a good fit for the data. Paired with the low BIC, this model is a good fit for this data.

One of the limitations of this study is the lack of uniform strategy among coaches. Different coaches will have different tendencies. During the time of this study, many coaches moved positions within the National Hockey League. Some were fired and some retired. Different coaches all have different strategies. Certain coaches, like Patrick Roy or John Cooper, have been known for their aggressive strategies when trailing. Other coaches might wait until the last second to make the decision. The different philosophies can create disparities among teams when compared to other optimal game theory discussed in other sports like American football (Psajdl, 2021). There can be clear factors that influence optimal decision making in those sports and it can be spotted within the data. The free-flowing nature of the sport of hockey can make it hard to implement exact optimal strategy for all teams in all situations.

Another limitation is the focus only on one goal games within the research. Teams can pull their goalie in any game at any time. This study only focuses on the one goal games as they are the simplest to identify a definitive optimal time to pull. Many times, desperate teams will pull earlier but it can result in the game getting further out of hand with empty net goals being scored at a higher rate. The higher variance was ignored for this study but can be addressed in future research as well.

The variables within the model are a limitation as well. GFA and GAA are basic controls for a team's offensive and defensive capabilities. These are estimates for team qualities and may not capture the full picture of a team's quality. There could be other factors as well that influence a team's chances to score a goal in the closing moments. OptimalPullPercent (OPP) is a crude way to identify the success rate as well. It was chosen to help account for the different strategies and assumes that teams will pull. It does not account for the times where teams are forced to wait to pull their goalie due to pace of play concerns.

Similar to the coarse instruments in the model, this study does not focus on the game level. This study assumed that all pull scenarios were the same across all games within a season. Each game is different on the ice and means something different closer to the end of the season as the playoffs approach. Future research could include the different game states and players who are on the ice during that time. Included in the game analysis level could be the team specific focus. An example would be the players that would be on the ice for a six on five scenario.

## **Conclusion**

Although the null hypothesis could not be rejected, the main finding from this study is that pulling the goalie does not improve the expected points added during the regular season or the likelihood a team will qualify for post-season play. Pulling the goalie is a widely accepted, high risk, high reward strategy to try to salvage a point in the standings. This study casts doubt on the long-term value of the strategy. Teams and coaches should begin looking for other strategies as well as they continue their quest for Lord Stanley's Cup.

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## Appendix A

The following code is what was used for the analysis.

```
## Installing necessary packages
{
install.packages(tidyverse)
install.packages(hockeyR)
install.packages(magrittr)
install.packages(fixest)
install.packages("modelssummary")
library(tidyverse)
library(hockeyR)
library(magrittr)
library(fixest)
library(modelssummary)
}

## Filtering Data For Analysis
# 17-18 Season
{
# Filtering data
pbp1718 <- load_pbp('2017-2018')
pbp1718$gd <- abs(pbp1718$home_score - pbp1718$away_score)
enPBP1718 <- pbp1718 %>%
  filter(season_type == "R",
         game_seconds_remaining <= 300,
         period == 3,
         event_type != "STOP",
         strength_state == "6v5",
         !is.na(event_team)) |>
  filter(row_number() == 1, .by = c(season, game_id, event_team_abbr))

optimal1718 <- enPBP1718 |>
  mutate(is_optimal_criteria = game_seconds_remaining <= 180 & gd == 1 & strength_state
         == "6v5") |>
  summarize(
    optimal_pulls = sum(is_optimal_criteria, na.rm = TRUE),
    non_optimal_pulls = sum(!is_optimal_criteria, na.rm = TRUE),
    .by = c(event_team_abbr)
  )

points1718 <- get_team_records(2018) %>%
  mutate(team = ifelse(team_abbr == "VEG", "VGK", team_abbr)) %>%
  select(team, st_points)
```



```

playoffs1718 <- pbp1718 |>
  group_by(team = event_team_abbr) |>
  summarize(
    gp = length(unique(game_id)),
    playoffs = ifelse(gp > 82, 1, 0)
  ) |>
  select(team, playoffs)

GFGA1718 <- pbp1718 |>
  filter(!is.na(event_team) & period < 5 & season_type == "R") |>
  group_by(team = event_team_abbr) |>
  summarise(
    gp = length(unique(game_id)),
    gf = sum(event_type == "GOAL"),
    .groups = "drop"
  ) |>
  left_join(
    pbp1718 |>
      filter(!is.na(event_team) & period < 5) |>
      mutate(team = ifelse(event_team_abbr == home_abbreviation, away_abbreviation,
        home_abbreviation)) |>
      group_by(team) |>
      summarise(
        ga = sum(event_type == "GOAL"),
        .groups = "drop"
      ),
    by = "team"
  )

en1718GameIDs <- enPBP1718$game_id
success1718 <- pbp1718 %>%
  filter(game_id %in% en1718GameIDs,
    period == 3,
    event_type == "PERIOD_END",
    gd == c("1", "2", "0"))
successCalc1718 <- success1718 |>
  mutate(successfulPullCalc = gd == 0) |>
  summarize(
    successfulPull = sum(successfulPullCalc, na.rm = TRUE),
    unsuccessfulPull = sum(!successfulPullCalc, na.rm = TRUE),
  )

# Joining filters
points1718 <- left_join(GFGA1718, points1718, by = "team")
playoffsGFGA1718 <- left_join(points1718, playoffs1718, by = "team")
final1718 <- left_join(playoffsGFGA1718, optimal1718, by = c("team" = "event_team_abbr"))

```

```

final1718$optimalPullPercent <-
  as.numeric(final1718$optimal_pulls/(final1718$optimal_pulls +
    final1718$non_optimal_pulls))
final1718$gfa <- (final1718$gf/final1718$gp)
final1718$gaa <- (final1718$ga/final1718$gp)
final1718$st_points <- as.numeric(final1718$st_points)
final1718 <- final1718 %>% select(-gp)
}

# 18-19 Season
{
# Filtering data
pbp1819 <- load_pbp('2018-2019')
pbp1819$gd <- abs(pbp1819$home_score - pbp1819$away_score)
enPBP1819 <- pbp1819 %>%
  filter(season_type == "R",
    game_seconds_remaining <= 300,
    period == 3,
    event_type != "STOP",
    strength_state == "6v5",
    !is.na(event_team)) |>
  filter(row_number() == 1, .by = c(season, game_id, event_team_abbr))

optimal1819 <- enPBP1819 |>
  mutate(is_optimal_criteria = game_seconds_remaining <= 180 & gd == 1 & strength_state ==
    "6v5") |>
  summarize(
    optimal_pulls = sum(is_optimal_criteria, na.rm = TRUE),
    non_optimal_pulls = sum(!is_optimal_criteria, na.rm = TRUE),
    .by = c(event_team_abbr)
  )

points1819 <- get_team_records(2019) %>%
  mutate(team = ifelse(team_abbr == "VEG", "VGK", team_abbr)) %>%
  select(team, st_points)

playoffs1819 <- pbp1819 |>
  group_by(team = event_team_abbr) |>
  summarize(
    gp = length(unique(game_id)),
    playoffs = ifelse(gp > 82, 1, 0)
  ) |>
  select(team, playoffs)

GFGA1819 <- pbp1819 |>
  filter(!is.na(event_team) & period < 5 & season_type == "R") |>

```

```

group_by(team = event_team_abbr) |>
summarise(
  gp = length(unique(game_id)),
  gf = sum(event_type == "GOAL"),
  .groups = "drop"
) |>
left_join(
  pbp1819 |>
  filter(!is.na(event_team) & period < 5) |>
  mutate(team = ifelse(event_team_abbr == home_abbreviation, away_abbreviation,
    home_abbreviation)) |>
  group_by(team) |>
  summarise(
    ga = sum(event_type == "GOAL"),
    .groups = "drop"
  ),
  by = "team"
)

```

#### # Successful Pull Calcs

```

en1819GameIDs <- enPBP1819$game_id
success1819 <- pbp1819 %>%
  filter(game_id %in% en1819GameIDs,
    period == 3,
    event_type == "PERIOD_END",
    gd == c("1", "2", "0"))
successCalc1819 <- success1819 |>
  mutate(successfulPullCalc = gd == 0) |>
  summarize(
    successfulPull = sum(successfulPullCalc, na.rm = TRUE),
    nonsuccessfulPull = sum(!successfulPullCalc, na.rm = TRUE),
  )

```

#### # Joining filters

```

points1819 <- left_join(GFGA1819, points1819, by = "team")
playoffsGFGA1819 <- left_join(points1819, playoffs1819, by = "team")
final1819 <- left_join(playoffsGFGA1819, optimal1819, by = c("team" = "event_team_abbr"))
final1819$optimalPullPercent <- as.numeric(final1819$optimal_pulls/(final1819$optimal_pulls
  + final1819$non_optimal_pulls))
final1819$gfa <- (final1819$gf/final1819$gp)
final1819$gaa <- (final1819$ga/final1819$gp)
final1819$st_points <- as.numeric(final1819$st_points)
final1819 <- final1819 %>% select(-gp)
}

```

#### # 19-20 Season

```

{
# Filtering data
pbp1920 <- load_pbp('2019-2020')
pbp1920$gd <- abs(pbp1920$home_score - pbp1920$away_score)
enPBP1920 <- pbp1920 %>%
  filter(season_type == "R",
         game_seconds_remaining <= 300,
         period == 3,
         event_type != "STOP",
         strength_state == "6v5",
         !is.na(event_team)) |>
  filter(row_number() == 1, .by = c(season, game_id, event_team_abbr))

optimal1920 <- enPBP1920 |>
  mutate(is_optimal_criteria = game_seconds_remaining <= 180 & gd == 1 & strength_state
         == "6v5") |>
  summarize(
    optimal_pulls = sum(is_optimal_criteria, na.rm = TRUE),
    non_optimal_pulls = sum(!is_optimal_criteria, na.rm = TRUE),
    .by = c(event_team_abbr)
  )

points1920 <- get_team_records(2020) %>%
  mutate(team = ifelse(team_abbr == "VEG", "VGK", team_abbr)) %>%
  select(team, st_points)

GFGA1920 <- pbp1920 |>
  filter(!is.na(event_team) & period < 5 & season_type == "R") |>
  group_by(team = event_team_abbr) |>
  summarise(
    gp = length(unique(game_id)),
    gf = sum(event_type == "GOAL"),
    .groups = "drop"
  ) |>
  left_join(
    pbp1920 |>
      filter(!is.na(event_team) & period < 5) |>
      mutate(team = ifelse(event_team_abbr == home_abbreviation, away_abbreviation,
                           home_abbreviation)) |>
      group_by(team) |>
      summarise(
        ga = sum(event_type == "GOAL"),
        .groups = "drop"
      ),
    by = "team"
  )
}

```

```

# Successful Pull Calcs
en1920GameIDs <- enPBP1920$game_id
success1920 <- pbp1920 %>%
  filter(game_id %in% en1920GameIDs,
         period == 3,
         event_type == "PERIOD_END",
         gd == c("1", "2", "0"))
successCalc1920 <- success1920 |>
  mutate(successfulPullCalc = gd == 0) |>
  summarize(
    successfulPull = sum(successfulPullCalc, na.rm = TRUE),
    nonsuccessfulPull = sum(!successfulPullCalc, na.rm = TRUE),
  )

# Joining filters
points1920 <- left_join(GFGA1920, points1920, by = "team")
final1920 <- left_join(points1920, optimal1920, by = c("team" = "event_team_abbr"))
# Hardcode playoffs to first round teams, excluding qualifying round
playoffTeams2020 <- c("PHI", "MTL", "TBL", "CBJ", "WSH", "NYI", "BOS", "CAR",
  "VGK", "CHI", "COL", "ARI", "DAL", "CAL", "STL", "VAN")
final1920$playoffs <- 0
final1920$playoffs[final1920$team %in% playoffTeams2020] <- 1
final1920$optimalPullPercent <-
  as.numeric(final1920$optimal_pulls/(final1920$optimal_pulls +
  final1920$non_optimal_pulls))
final1920$gfa <- (final1920$gf/final1920$gp)
final1920$gaa <- (final1920$ga/final1920$gp)
final1920$st_points <- as.numeric(final1920$st_points)
final1920 <- final1920 %>% select(-gp)
}

# 20-21 Season
{
  # Filtering data
  pbp21 <- load_pbp('2021')
  pbp21$gd <- abs(pbp21$home_score - pbp21$away_score)
  enPBP21 <- pbp21 %>%
    filter(season_type == "R",
          game_seconds_remaining <= 300,
          period == 3,
          event_type != "STOP",
          strength_state == "6v5",
          !is.na(event_team)) |>
    filter(row_number() == 1, .by = c(season, game_id, event_team_abbr))
}

```

```

optimal21 <- enPBP21 |>
  mutate(is_optimal_criteria = game_seconds_remaining <= 180 & gd == 1 & strength_state
         == "6v5") |>
  summarize(
    optimal_pulls = sum(is_optimal_criteria, na.rm = TRUE),
    non_optimal_pulls = sum(!is_optimal_criteria, na.rm = TRUE),
    .by = c(event_team_abbr)
  )

```

```

points21 <- get_team_records(2021) %>%
  mutate(team = ifelse(team_abbr == "VEG", "VGK", team_abbr)) %>%
  select(team, st_points)

```

```

playoffs21 <- pbp21 |>
  group_by(team = event_team_abbr) |>
  summarize(
    gp = length(unique(game_id)),
    playoffs = ifelse(gp > 56, 1, 0)
  ) |>
  select(team, playoffs)

```

```

GFGA21 <- pbp21 |>
  filter(!is.na(event_team) & period < 5 & season_type == "R") |>
  group_by(team = event_team_abbr) |>
  summarise(
    gp = length(unique(game_id)),
    gf = sum(event_type == "GOAL"),
    .groups = "drop"
  ) |>
  left_join(
    pbp21 |>
      filter(!is.na(event_team) & period < 5) |>
      mutate(team = ifelse(event_team_abbr == home_abbreviation, away_abbreviation,
                           home_abbreviation)) |>
      group_by(team) |>
      summarise(
        ga = sum(event_type == "GOAL"),
        .groups = "drop"
      ),
    by = "team"
  )

```

```

# Successful Pull Calcs
en21GameIDs <- enPBP21$game_id
success21 <- pbp21 %>%
  filter(game_id %in% en21GameIDs,

```

```

    period == 3,
    event_type == "PERIOD_END",
    gd == c("1", "2", "0"))
successCalc21 <- success21 |>
  mutate(successfulPullCalc = gd == 0) |>
  summarize(
    successfulPull = sum(successfulPullCalc, na.rm = TRUE),
    unsuccessfulPull = sum(!successfulPullCalc, na.rm = TRUE),
  )

# Joining filters
points21 <- left_join(GFGA21, points21, by = "team")
playoffsGFGA21 <- left_join(points21, playoffs21, by = "team")
final21 <- left_join(playoffsGFGA21, optimal21, by = c("team" = "event_team_abbr"))
final21$optimalPullPercent <- as.numeric(final21$optimal_pulls/(final21$optimal_pulls +
  final21$non_optimal_pulls))
final21$gfa <- (final21$gf/final21$gp)
final21$gaa <- (final21$ga/final21$gp)
final21$st_points <- as.numeric(final21$st_points)
final21 <- final21 %>% select(-gp)
}

# 21-22 Season
{
  # Filtering data
  pbp2122 <- load_pbp('2021-2022')
  pbp2122$gd <- abs(pbp2122$home_score - pbp2122$away_score)
  enPBP2122 <- pbp2122 %>%
    filter(season_type == "R",
           game_seconds_remaining <= 300,
           period == 3,
           event_type != "STOP",
           strength_state == "6v5",
           !is.na(event_team)) |>
    filter(row_number() == 1, .by = c(season, game_id, event_team_abbr))

  optimal2122 <- enPBP2122 |>
    mutate(is_optimal_criteria = game_seconds_remaining <= 180 & gd == 1 & strength_state
           == "6v5") |>
    summarize(
      optimal_pulls = sum(is_optimal_criteria, na.rm = TRUE),
      non_optimal_pulls = sum(!is_optimal_criteria, na.rm = TRUE),
      .by = c(event_team_abbr)
    )

  points2122 <- get_team_records(2022) %>%

```

```
mutate(team = ifelse(team_abbr == "VEG", "VGK", team_abbr)) %>%
select(team, st_points)
```

```
playoffs2122 <- pbp2122 |>
  group_by(team = event_team_abbr) |>
  summarize(
    gp = length(unique(game_id)),
    playoffs = ifelse(gp > 82, 1, 0)
  ) |>
  select(team, playoffs)
```

```
GFGA2122 <- pbp2122 |>
  filter(!is.na(event_team) & period < 5 & season_type == "R") |>
  group_by(team = event_team_abbr) |>
  summarise(
    gp = length(unique(game_id)),
    gf = sum(event_type == "GOAL"),
    .groups = "drop"
  ) |>
  left_join(
    pbp2122 |>
      filter(!is.na(event_team) & period < 5) |>
      mutate(team = ifelse(event_team_abbr == home_abbreviation, away_abbreviation,
        home_abbreviation)) |>
      group_by(team) |>
      summarise(
        ga = sum(event_type == "GOAL"),
        .groups = "drop"
      ),
    by = "team"
  )
```

```
# Successful Pull Calcs
en2122GameIDs <- enPBP2122$game_id
success2122 <- pbp2122 %>%
  filter(game_id %in% en2122GameIDs,
    period == 3,
    event_type == "PERIOD_END",
    gd == c("1", "2", "0"))
successCalc2122 <- success2122 |>
  mutate(successfulPullCalc = gd == 0) |>
  summarize(
    successfulPull = sum(successfulPullCalc, na.rm = TRUE),
    unsuccessfulPull = sum(!successfulPullCalc, na.rm = TRUE),
  )
```



```

# Joining filters
points2122 <- left_join(GFGA2122, points2122, by = "team")
playoffsGFGA2122 <- left_join(points2122, playoffs2122, by = "team")
final2122 <- left_join(playoffsGFGA2122, optimal2122, by = c("team" = "event_team_abbr"))
final2122$optimalPullPercent <-
  as.numeric(final2122$optimal_pulls/(final2122$optimal_pulls +
    final2122$non_optimal_pulls))
final2122$gfa <- (final2122$gf/final2122$gp)
final2122$gaa <- (final2122$ga/final2122$gp)
final2122$st_points <- as.numeric(final2122$st_points)
final2122 <- final2122 %>% select(-gp)
}

# 22-23 Season
{
  # Filtering data
  pbp2223 <- load_pbp('2022-2023')
  pbp2223$gd <- abs(pbp2223$home_score - pbp2223$away_score)
  enPBP2223 <- pbp2223 %>%
    filter(season_type == "R",
      game_seconds_remaining <= 300,
      period == 3,
      event_type != "STOP",
      strength_state == "6v5",
      !is.na(event_team)) |>
    filter(row_number() == 1, .by = c(season, game_id, event_team_abbr))

  optimal2223 <- enPBP2223 |>
    mutate(is_optimal_criteria = game_seconds_remaining <= 180 & gd == 1 & strength_state
      == "6v5") |>
    summarize(
      optimal_pulls = sum(is_optimal_criteria, na.rm = TRUE),
      non_optimal_pulls = sum(!is_optimal_criteria, na.rm = TRUE),
      .by = c(event_team_abbr)
    )

  points2223 <- get_team_records(2023) %>%
    mutate(team = ifelse(team_abbr == "VEG", "VGK", team_abbr)) %>%
    select(team, st_points)

  playoffs2223 <- pbp2223 |>
    group_by(team = event_team_abbr) |>
    summarize(
      gp = length(unique(game_id)),
      playoffs = ifelse(gp > 82, 1, 0)
    ) |>

```

```

select(team, playoffs)

GFGA2223 <- pbp2223 |>
  filter(!is.na(event_team) & period < 5 & season_type == "R") |>
  group_by(team = event_team_abbr) |>
  summarise(
    gp = length(unique(game_id)),
    gf = sum(event_type == "GOAL"),
    .groups = "drop"
  ) |>
  left_join(
    pbp2223 |>
      filter(!is.na(event_team) & period < 5) |>
      mutate(team = ifelse(event_team_abbr == home_abbreviation, away_abbreviation,
        home_abbreviation)) |>
      group_by(team) |>
      summarise(
        ga = sum(event_type == "GOAL"),
        .groups = "drop"
      ),
    by = "team"
  )

# Successful Pull Calcs
en2223GameIDs <- enPBP2223$game_id
success2223 <- pbp2223 %>%
  filter(game_id %in% en2223GameIDs,
    period == 3,
    event_type == "PERIOD_END",
    gd == c("1", "2", "0"))
successCalc2223 <- success2223 |>
  mutate(successfulPullCalc = gd == 0) |>
  summarize(
    successfulPull = sum(successfulPullCalc, na.rm = TRUE),
    nonsuccessfulPull = sum(!successfulPullCalc, na.rm = TRUE),
  )

# Joining filters
points2223 <- left_join(GFGA2223, points2223, by = "team")
playoffsGFGA2223 <- left_join(points2223, playoffs2223, by = "team")
final2223 <- left_join(playoffsGFGA2223, optimal2223, by = c("team" = "event_team_abbr"))
final2223$optimalPullPercent <-
  as.numeric(final2223$optimal_pulls/(final2223$optimal_pulls +
    final2223$non_optimal_pulls))
final2223$gfa <- (final2223$gf/final2223$gp)
final2223$gaa <- as.numeric(final2223$ga/final2223$gp)

```

```

final2223$st_points <- as.numeric(final2223$st_points)
final2223 <- final2223 %>% select(-gp)
}

## Analysis
# Formulas
{
  panelFormula <- st_points ~ optimalPullPercent + gfa + gaa | team
  logitFormula <- playoffs ~ optimalPullPercent + gfa + gaa | team
}

# Regressions and Histograms
{
  allyears <- bind_rows(final1718, final1819, final1920, final21, final2122, final2223)
  allSuccess <- bind_rows(successCalc1718, successCalc1819, successCalc1920, successCalc21,
    successCalc2122, successCalc2223)
  successRate <- (sum(allSuccess$successfulPull)/sum(allSuccess$nonsuccessfulPull)) * 100
  print(successRate)
# Summary stats
summary(allyears)
sdList <- list("gfa"=sd(allyears$gfa), "gaa"=sd(allyears$gaa),
  "optimal_pulls"=sd(allyears$optimal_pulls),
  "non_optimal_pulls"=sd(allyears$non_optimal_pulls),
  "optimalPullPercent"=sd(allyears$optimalPullPercent),
  "st_points"=sd(allyears$st_points), "playoffs"=sd(allyears$playoffs),
  "gf"=sd(allyears$gf), "ga"=sd(allyears$ga))
print(sdList)

# Panel Regression with Team Fixed Effects
panelReg <- feols(panelFormula, data = allyears)
summary(panelReg)

# Logit Panel Regression
logitReg <- feglm(logitFormula, data = allyears)
summary(logitReg)
# Transform beta to odds ratio
exp(logitReg$coefficients)

## Histograms
#optimal Pulling Percentage
hist(allyears$optimalPullPercent,
  main = "Histogram of Optimal Pull Percentage",
  xlab = "Optimal Pull Percentage",
  ylab = "Frequency",
  border = "white", # Add a white border to bars for better visibility
  breaks = 20 # Adjust the number of bins as needed

```

```
)  
  
playoffAvg <- allyears %>%  
  filter(playoffs == 1)  
averagePointsQual <- mean(playoffAvg$st_points)  
  
hist(allyears$st_points,  
     main = "Histogram of Standing Points",  
     xlab = "Standing Points",  
     ylab = "Frequency",  
     border = "white",  
     breaks = 20,  
     )  
abline(v = averagePointsQual, col = "black", lwd = 2)  
  
# Normality Tests  
ks.test(allyears$optimalPullPercent, "pnorm", mean = mean(allyears$optimalPullPercent), sd =  
        sd(allyears$optimalPullPercent))  
ks.test(allyears$st_points, "pnorm", mean = mean(allyears$st_points), sd =  
        sd(allyears$st_points))  
}
```