Analyzing Scoring Chance Events Created by Passes in Women's Ice Hockey

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Abstract

One-timers are one of the most exciting plays in ice hockey. After analyzing 34 women's ice hockey games with pass and shot data, I found that one-timers create significant increases in probability of scoring a goal, as well as passes through the middle of the ice. Goal distance with the most significant indictor of whether a shot would result in a goal. Shots taken inside "the house" had much higher goal scoring rates than shots outside "the house". These differences with enlarged if the shot was a one-timer and/or included a pass through the middle of the ice.

1. Introduction

As ice hockey leagues and teams, especially the NHL, continue to rapidly increase their player tracking, data collection, and access to such data, there are more and more insights found on how the game is played, which teams are predicted to be the most talented, how much individual players contribute to their team, and so on. While ice hockey data analytics are growing, there are still many unanswered questions. Until recently, passing data in all hockey leagues was not openly accessible. Considering how crucial passing is in hockey, not having this data caused a big disconnect between how ice hockey is played and the inferences that could be made using data.

In ice hockey, a primary assist is awarded to the player that made the last pass or applicable play before a goal was scored for his or her team (National Hockey League 2022). A secondary assist is awarded to the player that passed or made an applicable play to the player who was awarded the primary assist(National Hockey League 2022). Both primary and secondary assists are worth the same, one point(National Hockey League 2022). One point is also awarded to the player who scored the goal. Sometimes primary assists (and even secondary assists) are made so perfectly that the goal scorer does not have to do much to score; they merely need to tap the puck into the net. On the other hand, the primary and/or secondary may not be very skillful. Regardless, the points awarded for these different difficulty plays are the same. Therefore, goals, assists, and points do not tell us very much about how important or valuable a particular play was in creating a goal.

In terms of plays that create goals, there are three passing play types that tend to create high-quality scoring opportunities: passes that create one-timer shots, passes that go through the midline of the offensive zone and create a shot, and passes from behind the goal line to a shooter in front of the net.

My focus will be on the one-timer, or a shot taken without settling the puck down when receiving a pass, which can be one of the most exciting and high-quality opportunities("What Is A One-Timer In Hockey? Definition & Meaning On SportsLingo" n.d.). A one-timer can be shot even harder than a slapshot by the most skilled players, and since the shot is taken immediately after a pass, the shooter can often shoot before the goalie has moved into the correct position to stop the shot. Therefore, one-timers are known to create high-quality scoring chances often. Some players such as Alex Ovechkin have made a living perfecting their one-timer to the point where it almost feels like it will be an automatic goal for his team when he takes a one-timer.

Building on previous research, I would like to contribute to the existing literature on passing in ice hockey by answering the following questions:

1. How different are the shooting percentages of one-timers in women's hockey, as compared to non-one-timers and quick shots taken right after receiving a pass?

2. For non-one-timers, do quick shots taken right after receiving a pass have similar or different shooting percentages?

3. How big of a difference does a pass through the midline of the ice before a shot or a pass that originates behind the net affect the shooting percentages of one-timers, non-one-timers, and quick shots taken right after receiving a pass?

This paper builds on current research by:

1. Improving the understanding of the value of a specific events in ice hockey, namely the one-timer, passing through the midline of the ice, and passes originating from behind the offensive goal.

2. Improving the current expected goals models in ice hockey.

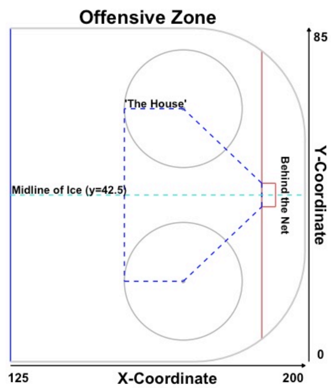
1.1 Key Terms and Definitions

Below are a list of key terms and definitions that are essential in understanding the rest of this paper.

- **One-timer:** When an offensive ice hockey player immediately meets their teammate's pass with a slap shot without stopping the puck or trying to handle the puck in any way. Although a slap shot is the most common way to hit a one timer, a wrist shot can also be used, but it tends to be a slower shot ("What Is A One-Timer In Hockey? Definition & Meaning On SportsLingo" n.d.). A dummy logical TRUE/FALSE variable was created to track this shot type, called "one_timer".
- **"Royal Road" pass/ Midline pass:** A line that goes directly through the middle of the ice from one net to the other. It separates the ice into two equal parts. A pass made across this line in the offensive zone is considered a Royal Road pass (Boyle 2019). A dummy logical TRUE/FALSE variable was created to track whether a shot was taken after this pass type, called "through_middle _shot".
- **Behind net pass:** Also known as a low-to-high pass. When an attacking player makes a pass from behind the goal line of the opposing team to a teammate also in offensive zone but not behind the net (Stimson 2016). A dummy logical TRUE/FALSE variable was created to track whether a shot was taken after this pass type, called "behind_net_shot".
- **Quick shot/ Catch and Release Shot:** A shot taken immediately after receiving a pass, but not a one-timer. These types of shots have similar positive attributes as one-timers such as the advantage of quickly letting a shot go before the goalie has adjusted their position, but does not have the advantage of shooting a harder shot compared to a regular

shot. A dummy logical TRUE/FALSE variable was created to track this shot type, called "shot_after_pass".

- **Shot Percentage:** The number of shots that result in goals divided by the number of total shots.
- **Traffic:** Whether there are player(s) in between the shooter and goalie. It is harder for the goalie to see the puck with traffic, but it is also harder for the shooter to hit the net as it is more likely they will have their shot blocked or miss the net. This is a logical TRUE/FALSE variable in my dataset.
- **Advantage:** The number of skaters on the ice for the offensive team minus the number of skaters for the defensive team. A positive advantage means the offensive team has more skaters than the defensive team and thus a higher probability of scoring. A negative advantage means the offensive team has less skaters than the defensive team and thus a lower probability of scoring. This is a ordinal variable in my dataset with a range of -2 to +2.



2. Literature Review

Data analytics in ice hockey has only recently become an important part of recruiting players, improving team strategy, finding weaknesses and strengths, and so on. Hockey analytics also has begun to be incorporated into other parts of the game, including the media, creating new revenue streams through licensing and sponsoring the data and fantasy hockey, and viewer interaction, interest, acquisition, and retention (Tran 2021). Hockey data analytics first looked at goals simply by examining the number of shots and goals for individuals, teams, etc. Analysis evolved to look deeper into quantifying scoring chances through shot attempts (Corsi), unblocked shot attempts (Fenwick), and expected goals (xG) (Morse 2022). While these measures improved the understanding of scoring chances, there were still a lot of essential variables left unaccounted for, causing these measures to be better than only looking at shots or goals, but still not amazing at understanding the offensive power of teams or individuals. From here, a lot of current ice hockey research has used tools built from other sports, such as expected threat (xT) (Singh n.d.). The expected threat metric uses an improved model that accounts for the chain of events before a shot is taken and how each event either improves or worsens the chance of a shot and/or goal. By dividing the ice rink into smaller areas, each area can be given an xT coefficient. By looking at how much passing or moving into a different area, we can create a metric (xT) for how threatening that move was (Singh n.d.).

Howell (2021) transformed this metric originating in soccer and transformed it to create a similar xT model for ice hockey, calling it expected attack value or xAV. From here, he was able to find the top players who create the most offense by shooting in high xAV areas or moving and passing from a lower xAV area into a higher xAV area. While the xAV model is arguably the most detailed and accurate model for ice hockey offense as of now, it does not account for shot type, the time between a pass and shot, whether there is traffic in front of the shot, and simply values passes on whether they are completed and if the pass improves the attack value by passing into a higher xAV area. In terms of calculating how many goals a player or team should score in a given situation, this is an excellent model, but it is not great for valuing the passes to create a scoring opportunity in a high xAV area, and certainly undervalues difficult passes made that become one-timers.

Ryan Stimson from hockeygraphs.com first attempted to quantify the importance of one-timers by looking at the main difference between regular shots and one-timers. The biggest difference was the probability of a goal with an on-net shot, where the one-timer has an 11.3% chance of scoring, while a regular wrist shot only has a 6.8% chance of scoring (Stimson 2017). Interestingly, one-timer shots had a similar repeatability coefficient as slap shots (.55 vs .54 Pearson R), and one-timer shots had the highest Pearson R-value in predicting future goal scoring out of any shot type (Stimson 2017). Looking at passes to create one-timers, both the repeatability and future prediction of assists look very similar to the R-values found in one-timer shots. Lastly, both one-timer shots and passes to create one-timers are more predictive of future goal-scoring and assists than any other predictive metric tested (Stimson 2017).

Arik Parnass also broke down Ryan Stimson's passing data, finding that one-timers are significantly more dangerous in terms of scoring than any other shot. One-timers from the perimeter of the rink tend to be less effective than other shot types from the perimeter, which should be accounted for when valuing passes to create one-timers (Parnass 2016).

One other area that tends to generate high-quality scoring chances is passes that come from behind the goal line to a shooter in front of the net. In a 2016 article by loserpoints, NHL shots after passes from behind the net had a 6.73% shooting percentage, and NHL shots after passes through the midline of the ice had a 15.5% shooting percentage (loserpoints 2016). These numbers came from analyzing over 500 NHL games. An article in MSG networks blog found that 22% of all goals in a 100 NHL-game dataset came after passes across the “Royal Road”, and 9% of all goals in the same dataset came from one-timers with passes completed on the same side of the “Royal Road” (“The (Royal) Road to the Future of Goaltender Analytics” 2015). Shots inside “the house” also had a 300% greater success rate than shots outside “the house” (“The (Royal) Road to the Future of Goaltender Analytics” 2015). Lastly, green goals, or plays where the goaltender has a limited time to set their depth and angle and had less than 0.5 seconds to track an incoming shot, accounted for 76% of goals (“The (Royal) Road to the Future of Goaltender Analytics” 2015).

Unsurprisingly, only 13.2% of all shots in the NHL came after a “Royal Road” pass (Sznajder 2021). This is likely due to the amount of effort defenseman put in preventing this pass considering how dangerous it is. Also, over 22% of all primary shot assists were low-to-high plays, or passes from behind the net, even though these plays only had about a 2% chance of resulting in a goal (Sznajder 2021). Sznajder (2021) suggests this is because hockey is such a quick game, and moving the puck from behind the net to further away from the net creates more time and space. On the other hand, while these shots have low scoring probability, deflections havea 30% shooting percentage, so even though shots from far away have low chances of going straight in, if they cause a deflection they become a high-quality chance (Sznajder 2021).

Alex Novet found this including pre-shot movement in an expected goals model greatly improved the accuracy of the model, but goal distance was still by far the most important variable in predicting if a shot would result in a goal (Novet 2019).

Ryan Stimson found that while one-timers have an overall shooting percentage of 4.8%, that shooting percentage rises to 11.3% if the one-timer is on net. Unfortuneatly, one-timers have a lower percentage of being shot on net and are less repeatable compared to other shot types (Stimson 2017).

Fluto Shinzawa emphasizes the low shooting percentage and shot on net percentage with one-timers. He found that even one-timers on the power-play did not have high a shooting percentage, 4.2% vs. 4.1% even strength (Shinzawa 2022). Only 0.6% of unscreened (shot without traffic) one-timers from about the tops of the circles score, and only 3.7% of rebounds off of one-timers scored (Shinzawa 2022). Shinzawa (2022) suggests that taking more wrist shots are a better solution, as teammates may be more willing to create traffic, create more options by having your head up with the puck, create more secondary chances, and break sticks less often.

3. Data and Methods

3.1 Data

I compiled the three datasets from the Stathletes *Bip Data Cup 2022***,** which includes data from the 2018 Women's Olympic Hockey Tournament, a selection of Women's NCAA hockey games, and games from the 2021 PHF COVID bubble ("Big Data Cup 2022" n.d.).

This dataset includes 13 teams from PHF, Olympic, and NCAA leagues, 34 total ice hockey games, and includes 4168 shot attempts. I chose to limit my data to the offensive zone and online include shots that are not fans or wrap-arounds. Below are descriptive statistics of the cleaned and filtered dataset.

Table 1: Descriptive Statistics for Shots and Goals

	Event Count	Event Goal Count	Shot Percentage
All Shots	4168	165	3.96%
House Shots	1487	124	8.34%
Non-House Shots	2681	41	1.53%
behind_net_shot	313	15	4.79%
through_middle_shot	809	48	5.93%
one_timer	507	39	7.69%
shot_after_pass	619	33	5.33%

Table 2: Games Played By League

league	Games Played
NCAA	2
olympic	17
phf	15

Table 3: Games Played By Team

Team	Games Played
Boston	7
Buffalo	6
Clarkson	2
Connecticut	4
Metropolitan	3
Minnesota	4
CAN	12
FIN	6
RUS	4
USA	9
St_Lawrence	2
Toronto	6
SWZ	3

3.2 High-Quality Pass Types

I will look at three key pass types in women's ice hockey, namely passes that create one-timers, passes that originate from behind the offensive net, and passes that cross the midline of the offensive zone. As described in the literature review section, these are the most dangerous plays in terms of creating scoring chances in the offensive zone.

3.3 Methods

I used a forward selection method multivariable logistic regression to assess the variables that contribute to predicting whether a goal is scored on a shot. I first start with a null model (Model 1). Model 2 includes the three passing types before a shot: one_timer, behind_net_shot, and through_middle_shot. Model 3 adds on to Model 2 by including shot_after_pass. Model 4 adds on to Model 3 by including goal_dist. Model 5 adds onto Model 4 by including shot_angle. Lastly, Model 6 adds onto Model 5 by including period_seconds, advantage, and traffic. Using the result of logistic regression to predict whether a shot is a goal or not creates an expected goals model, or xGoal model. The xGoal model that I have created is defined below.

$$\begin{aligned} xGoal \ = \ & \beta_0 + \beta_1\, one\ timer + \ \beta_2\, behind\ net\ shot + \ \beta_3\, through\ middle\ shot \\ & + \ \beta_4\, shot\ after\ pass + \ \beta_5\, goal\ dist + \ \beta_6\, shot\ angle + \ \beta_7\, period\ seconds \\ & + \ \beta_8\, advantage + \ \beta_9\, traffic + \ \epsilon \end{aligned}$$

4. Results

4.1 Descriptive Statistics

Table 4: Shooting Percentage of Events in "The House"

One-Timer	Shot After Pass	Shot after pass through midline	Shot after pass from behind the net	Shooting Percentage
FALSE	FALSE	FALSE	FALSE	7.14
FALSE	FALSE	FALSE	TRUE	2.94
FALSE	FALSE	TRUE	FALSE	3.75
FALSE	FALSE	TRUE	TRUE	0.00
FALSE	TRUE	FALSE	FALSE	4.72
FALSE	TRUE	FALSE	TRUE	0.00
FALSE	TRUE	TRUE	FALSE	14.94
FALSE	TRUE	TRUE	TRUE	28.57
TRUE	FALSE	FALSE	FALSE	7.14
TRUE	FALSE	FALSE	TRUE	15.62
TRUE	FALSE	TRUE	FALSE	18.67
TRUE	FALSE	TRUE	TRUE	11.11

Table 5: Shooting Percentage of Events not in "The House"

One-Timer	Shot After Pass	Shot after pass through midline	Shot after pass from behind the net	Shooting Percentage
FALSE	FALSE	FALSE	FALSE	1.07
FALSE	FALSE	FALSE	TRUE	1.09
FALSE	FALSE	TRUE	FALSE	1.34
FALSE	FALSE	TRUE	TRUE	0.00
FALSE	TRUE	FALSE	FALSE	1.85
FALSE	TRUE	FALSE	TRUE	0.00
FALSE	TRUE	TRUE	FALSE	6.77
FALSE	TRUE	TRUE	TRUE	0.00
TRUE	FALSE	FALSE	FALSE	2.16
TRUE	FALSE	FALSE	TRUE	0.00
TRUE	FALSE	TRUE	FALSE	2.63
TRUE	FALSE	TRUE	TRUE	0.00

Table 6: Difference in Shotting Percentage of events from "The House" and not from "The House"

One-Timer	Shot After Pass	Shot after pass through midline	Shot after pass from behind the net	Shooting Percentage Difference
FALSE	FALSE	FALSE	FALSE	6.07
FALSE	FALSE	FALSE	TRUE	1.85
FALSE	FALSE	TRUE	FALSE	2.41
FALSE	FALSE	TRUE	TRUE	0.00
FALSE	TRUE	FALSE	FALSE	2.87
FALSE	TRUE	FALSE	TRUE	0.00
FALSE	TRUE	TRUE	FALSE	8.17
FALSE	TRUE	TRUE	TRUE	28.57
TRUE	FALSE	FALSE	FALSE	4.98
TRUE	FALSE	FALSE	TRUE	15.62
TRUE	FALSE	TRUE	FALSE	16.04
TRUE	FALSE	TRUE	TRUE	11.11

Above is a table for the shooting percentage of each possible combination of shot and pass types. It is broken down into events in “the house”, events not in “the house”, and the difference in shooting percentage between events in “the house” and events not in “the house”.

The first observation to note is the difference in shooting percentage in row 8. Passes that come from behind the net, go through the middle of the ice, and result in a quick shot being taken have a very high chance of being scored on in “the house”, but no goals were observed if this pass was completed outside “the house”.

Secondly, shots that are one-timers have the biggest difference in shooting percentage when one-timers taken inside “the house” are compared to one-timers taken outside “the house”.

Third, passes that originate from behind the net seem to only create high-quality chances if they are completed inside “the house” and result in either a one-timer or quick shot. This occurs because the increased effect of completing a pass originating from the behind the net is only more effective than any other pass if it creates a shot quickly. Unlike a pass through the middle of the ice, the goalie does not need to adjust their positioning nearly as much with a pass from behind the net compared to a pass through the middle of the ice.

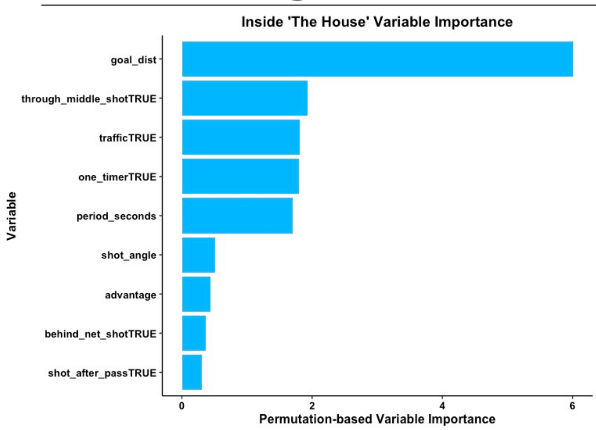
4.2 Results by Location

Below are three subsections with logistic regression results from Model 6 of each shot location (offensive zone, in “the house”, outside “the house”), converted into percent change in probability of scoring a goal, variable importance results, and goal scoring probability vs. goal distance plots. These results were found by running a logistic regression, then converting the log-odds results (see appendix 9.1 Logistic Regression Log-Odds Results) to percent change in predicted probabilities centered at 0. The result of this transformation gives us the percent change in probability of scoring a goal, holding all other variables constant. Variable Importance plots were found using the vip() function from the vip package in R. Probability of scoring a goal vs. goal distance plots were found by plotting continuous smoothed mean probabilities and 95% confidence intervals of scoring a goal at each distance from the goal.

4.2.1 House Events

Table 7: Percent Change in Probability Holding other Variables Constant for Model 6 House Events

	Coefficients (%)	SE (%)	Z-value	p-value
(Intercept)	-23.100%	7.784%	-2.967	0.003
one_timerTRUE	11.877%	6.702%	1.772	0.076
behind_net_shotTRUE	3.114%	8.319%	0.374	0.708
through_middle_shotTRUE	12.295%	6.475%	1.899	0.058
shot_after_passTRUE	2.369%	7.528%	0.315	0.753
goal_dist	-1.913%	0.318%	-6.006	0
shot_angle	0.066%	0.129%	0.509	0.611
period_seconds	-0.012%	0.007%	-1.705	0.088
trafficTRUE	-12.027%	6.738%	-1.785	0.074
advantage	-2.153%	4.870%	-0.442	0.658



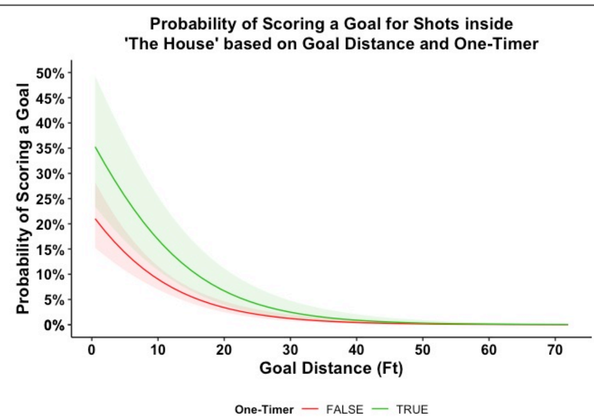


Table 7 outlines these results for all shots within “the house”. One-timers (one_timer), shots after a pass through the midline (through_middle_shotTRUE), and goal distance are all significant at $p < 0.05$. Time left in the period (period_seconds) and traffic (trafficTRUE) are significant at $p < 0.1$. Shots after passes from behind the net (behind_net_shotTRUE), quick shots (shot_after_passTRUE), shot angle (shot_angle), and advantage (advantage) were not statistically significant.

Taking a one-timer or shooting after a pass is completed through the midline within “the house” results in a similar increase in the probability of scoring a goal; around 12%. This was not a surprising result, but I was surprised that passes from behind the net did not change shooting probability within “the house” nearly as much.

For every foot that the shooter is away from the net, the probability of their shot scoring decreased by 1.91%. This is a big difference, considering the furthest point away from the net but still in “the house” is 41.34 ft away from the net. That mean a shot taken from the furthest point away from the net but still in “the house” has a ~80% lower probability of scoring a goal compared to a shot taken right on top of the goal line. Also, shots taken within “the house” with traffic result in a 12% lower scoring probability compared to shots taken without traffic.

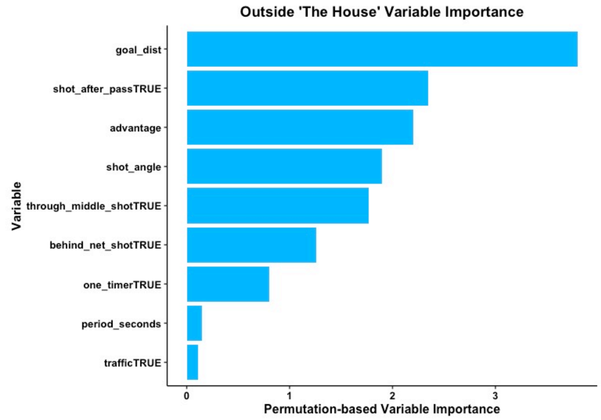
Lastly, for every second later in a period, the probability of scoring a goal within “the house” decreases by 0.012%. While this is a small reduction, it must be realized that there are 20 minutes in a period, or 1200 seconds. Therefore, a shot taken at the beginning of the period (period_seconds = 0) has a 14.4% (0.012% * 1200) higher probability of being scored compared to a shot taken at the end of the period (period_seconds = 1200). I theorize this is due to the difficulty of shooting a hard and accurate on “dirty” or chopped ice is compared to “clean” or fresh ice. As the period continues, the ice continues to have more and more ruts from skaters cutting into the ice, making it harder to receive a pass and shoot.

As seen in the variable importance plot, goal distance is the biggest predictor of scoring a goal within “the house”. Shots after passes through the midline, traffic, one-timers, and time left in the period all had similar importance in predicting whether a shot would result in a goal.

4.2.2 Non-House Events

Table 8: Percent Change in Probability Holding other Variables Constant for Model 6 Non-House Events

	Coefficients (%)	SE (%)	Z-value	p-value
(Intercept)	-46.84%	17.435%	-2.687	0.007
one_timerTRUE	28.20%	12.810%	2.202	0.028
behind_net_shotTRUE	-23.95%	24.180%	-0.991	0.322
through_middle_shotTRUE	25.69%	9.992%	2.571	0.01
shot_after_passTRUE	34.12%	10.238%	3.333	0.001
goal_dist	-1.76%	0.317%	-5.573	0
shot_angle	-0.22%	0.189%	-1.184	0.236
period_seconds	0.00%	0.012%	-0.348	0.728
trafficTRUE	29.52%	10.179%	2.9	0.004
advantage	8.11%	6.996%	1.159	0.247



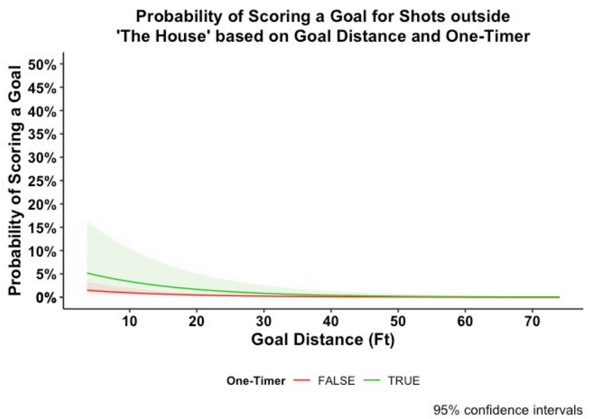


Table 8 outlines these results for all shots outside “the house”. One-timers (one_timer), shots after a pass through the midline (through_middle_shotTRUE), quick shots (shot_after_passTRUE), traffic (trafficTRUE), and goal distance are all significant at $p < 0.05$. Shots after passes from behind the net (behind_net_shotTRUE), shot angle (shot_angle), time left in the period (period_seconds), and advantage (advantage) were not statistically significant.

Taking a one-timer outside “the house” increases the probability of scoring a goal by 28%. It is important to note that the probability of scoring a goal outside “the house” is very low, therefore a 28% increase in probability in scoring a goal is not nearly as much as it sounds like. Once again, a shot after a pass through the midline creates a similar increase in probability in scoring a goal as it did inside “the house”. Outside “the house”, a shot after a pass through the midline results in a 25.7% increase in probability of scoring a goal.

We see a very similar relationship between change in probability of scoring a goal and goal distance outside “the house” as well. For every foot that the shooter is away from the net, the probability of their shot scoring decreased by 1.76% This is a big difference, considering the furthest point away from the net but outside “the house” is 76.8 ft away from the net. That mean a shot taken from the furthest point away from the net outside “the house” has close to a 0% chance of resulting in a goal.

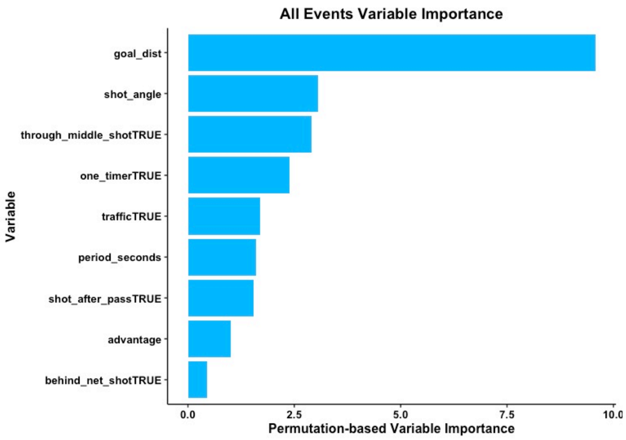
Shots with traffic have an inverse relationship in changes of goal scoring probability outside “the house” as compared to shot with traffic inside “the house”, as shots with traffic outside “the house” have close to a 30% increase in goal scoring probability. This is likely caused by the way players shoot inside vs. outside “the house”. When inside “the house”, players are shooting to hit their target accurately. Meanwhile, outside “the house”, players rely more on luck. Therefore, traffic in front a shooter outside the house helps as they may screen the goalie and/or tip the puck, making it more difficult for the goalie to make the save.

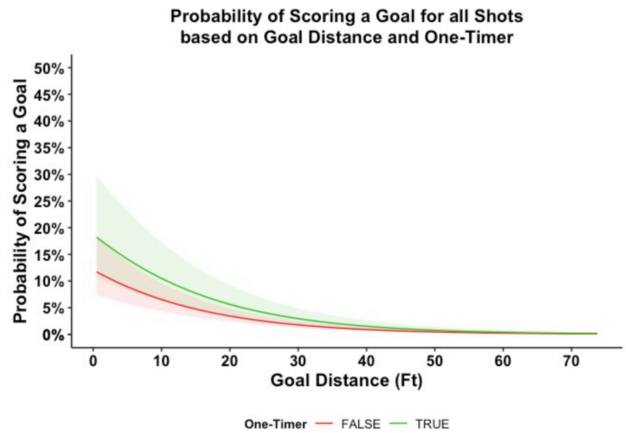
As seen in the variable importance plot, goal distance is again the biggest predictor of scoring a goal outside “the house”. Quick shots, advantage, shot angle, and shots after passes through the midline all had similar importance in predicting whether a shot would result in a goal.

4.2.3 All Events

Table 9: Percent Change in Probability Holding other Variables Constant for Model 6 All Events

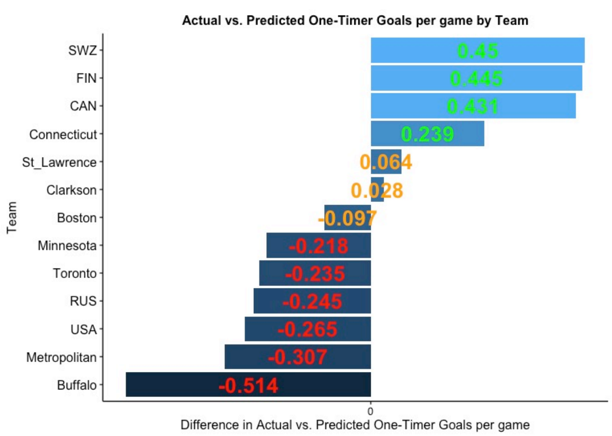
	Coefficients (%)	SE (%)	Z-value	p-value
(Intercept)	-22.70%	6.342%	-3.579	0
one_timerTRUE	13.42%	5.717%	2.347	0.019
behind_net_shotTRUE	-3.43%	7.547%	-0.454	0.65
through_middle_shotTRUE	14.61%	5.143%	2.84	0.005
shot_after_passTRUE	8.96%	5.821%	1.539	0.124
goal_dist	-1.70%	0.177%	-9.579	0
shot_angle	-0.28%	0.091%	-3.068	0.002
period_seconds	-0.01%	0.006%	-1.6	0.11
trafficTRUE	-8.81%	5.247%	-1.68	0.093
advantage	3.95%	3.922%	1.008	0.314

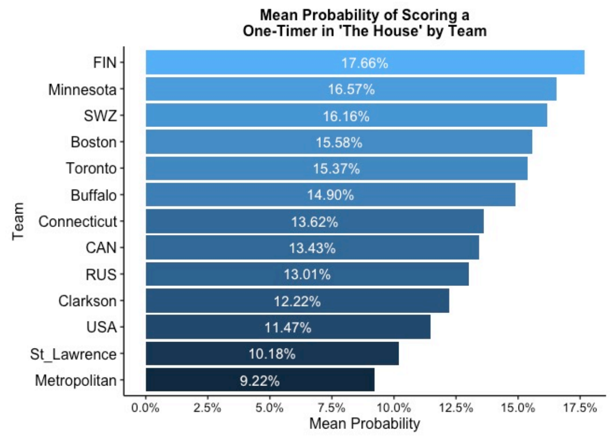


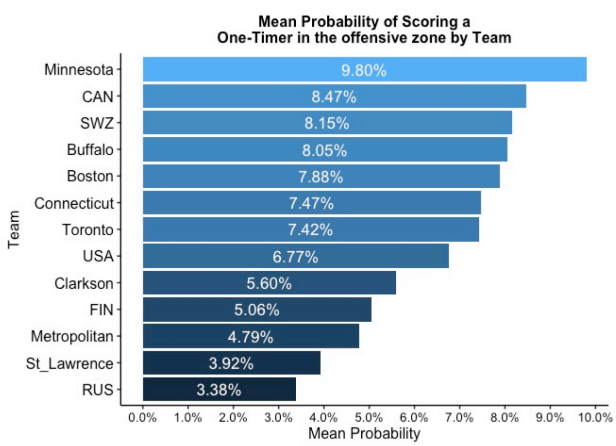


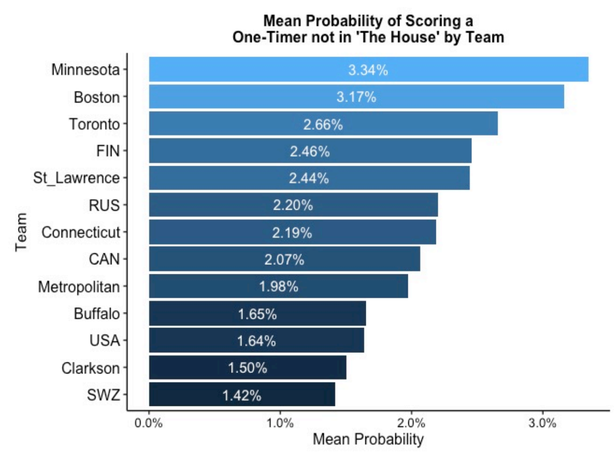
Removing whether the shot was in "the house", table 9 explains the results for any shot in the offensive zone. We can see that goal distance is once again very important. Shot angle, shots after passes through the middle, and one-timers are also important. We also see that one timers and shots after passes through the middle again have similar increases in probability of scoring a goal, around 13-14%. One-timers, shots after passes through the middle, goal distance, and shot angle are significant at $p < 0.05$. Traffic is significant at $p < 0.1$, and time left in the period is nearly significant at $p < 0.1$.

4.3 One-Timer Goal Scoring Probabilities by Team









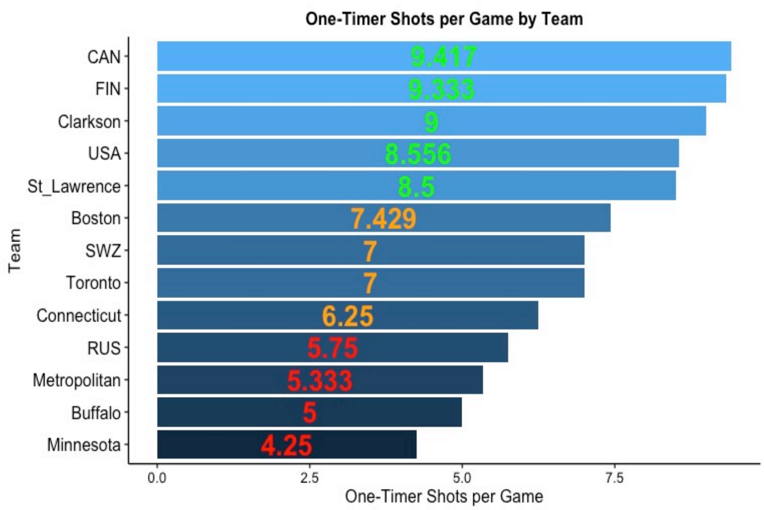
Unfortunately, there was not enough data to come up with definitive results on the way that one-timer scoring probabilities and one-timer actual vs. predicted scoring percentages could predict team records. Considering hockey falls more on the luck side of the luck-skill continuum (Vox 2017), we need a lot more games in the dataset to be able to predict team records using one-timer shooting percentages.

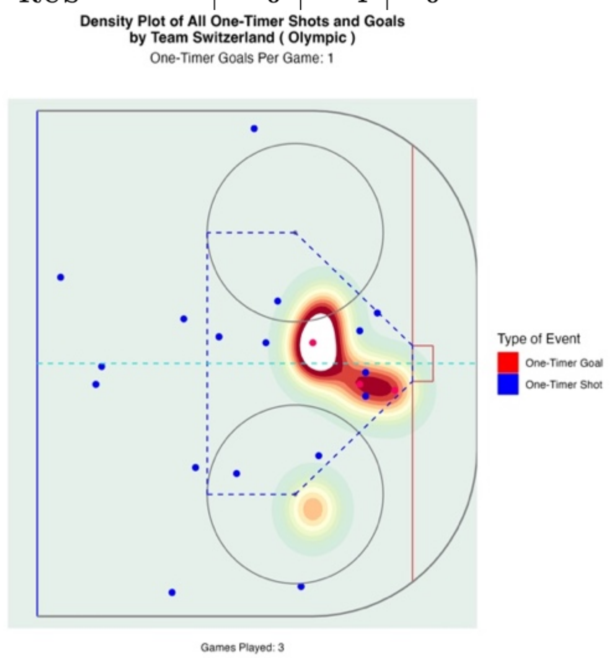
Switzerland's (SWZ) style of play in terms of one-timer shooting. While they do not take a particularly large number of one-timer shots per game (7 per game, which is right at median for all teams), they tend to take most of their one-timers close to the net.

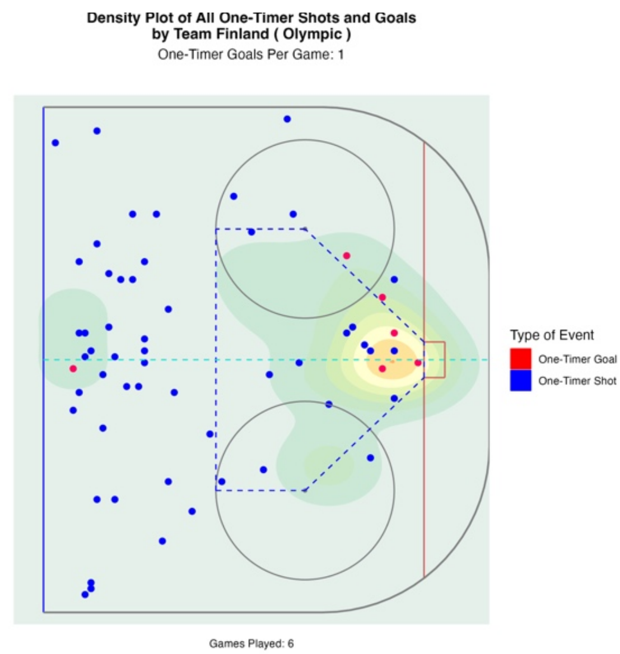
Canada (CAN) and Finland (FIN) tend to create their one-timer scoring chances by taking one-timers often, both averaging over 9 one-timer shots per game. Unlike Switzerland, a lot of Finland's one-timers come from far away from the net.

Team Records

team	win	loss	tie
Boston	3	4	0
Buffalo	1	4	1
CAN	8	3	1
Clarkson	1	1	0
Connecticut	1	2	1
FIN	3	2	1
Metropolitan	2	1	0
Minnesota	2	1	1
St_Lawrence	1	1	0
SWZ	1	2	0
tie	4	4	0
Toronto	4	1	1
USA	3	4	2
RUS	0	4	0







5. Conclusion and Implications

In conclusion, one-timers are statistically more advantageous than quick shots in “the house”, but the opposite is true outside “the house”. The distance from the net is by far the biggest predictor of whether a shot will result in a goal, followed by shot angle. A pass that goes through the midline to create a shot and one-timer passes create significantly higher scoring chances than regular shots without a pass or regular shots with a pass not through the midline. In general, any shot inside the pass will create a higher probability of a goal compared to even the highest-quality chances outside “the house”.

Therefore, teams and players should focus on creating opportunities to pass across the midline of the ice and look to create one-timers inside “the house”. One-timers are less effective outside “the house” and are also a more difficult shot to shoot on net. Therefore, to maintain the accuracy of a non-one-timer but maintain the advantage of having the goalie out of position, it is best to try and quickly catch and release a pass if outside of “the house”. For any shot type, once outside of 30 ft of the goal, goal scoring probability drops below 5%. Therefore, if players are outside 30 ft from the net, they should look to pass or shoot for a rebound to create a better opportunity than simply shooting to score.

The results from women’s ice hockey very closely resemble men’s ice hockey in terms of one-timer and “Royal Road” shot percentages. Therefore, this research could be applied to both men’s and women’s ice hockey.

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7. Appendix

7.1 Linear Regression Log-Odds Results

Table 1: Log-Odds of House Logistic Regression Models

	Dependent variable: goal					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(1)	(2)	(3)	(4)	(5)	(6)
one_timerTRUE	1.291***	0.948***	1.134***	0.751***	0.694**	0.717***
	(0.216)	(0.243)	(0.259)	(0.274)	(0.275)	(0.276)
behind_net_shotTRUE		0.406	0.285	0.181	0.185	0.190
		(0.323)	(0.327)	(0.340)	(0.340)	(0.342)
through_middle_shotTRUE		0.875***	0.687***	0.666**	0.655**	0.636**
		(0.232)	(0.250)	(0.268)	(0.268)	(0.269)
shot_after_passTRUE			0.590**	0.341	0.303	0.349
			(0.292)	(0.311)	(0.312)	(0.314)
goal_dist				−0.104***	−0.105***	−0.104***
				(0.011)	(0.011)	(0.012)
shot_angle					−0.007	−0.007
					(0.005)	(0.005)
period_seconds,						−0.0005*
						(0.0003)
trafficTRUE						−0.060
						(0.264)
advantage						−0.174
						(0.192)
Constant	−3.122***	−3.243***	−3.310***	−1.309***	−1.052***	−0.764**
	(0.107)	(0.116)	(0.123)	(0.200)	(0.262)	(0.306)
Observations	2,395	2,395	2,395	2,395	2,395	2,395
Log Likelihood	−473.028	−466.300	−464.401	−406.403	−405.318	−403.573
Akaike Inf. Crit.	950.056	940.600	938.802	824.806	824.636	827.145
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 2: Log-Odds of Non-House Logistic Regression Models

	Dependent variable: goal					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(1)	(2)	(3)	(4)	(5)	(6)
one_timerTRUE	1.774***	0.731	1.574***	1.689***	1.610***	1.278**
	(0.446)	(0.487)	(0.525)	(0.534)	(0.535)	(0.524)
behind_net_shotTRUE		−0.184	−0.581	−1.194	−1.060	−1.043
		(1.021)	(1.030)	(1.054)	(1.052)	(1.055)
through_middle_shotTRUE		2.192***	1.377***	1.623***	1.520***	1.136***
		(0.350)	(0.400)	(0.411)	(0.418)	(0.405)
shot_after_passTRUE			2.037***	2.040***	1.992***	1.668***
			(0.422)	(0.424)	(0.427)	(0.415)
goal_dist				−0.049***	−0.059***	−0.071***
				(0.010)	(0.011)	(0.013)
shot_angle					−0.013*	−0.009
					(0.007)	(0.008)
period_seconds,						−0.0002
						(0.0005)
trafficTRUE						1.357***
						(0.413)
advantage						0.327
						(0.282)
Constant	−5.551***	−5.873***	−6.066***	−4.216***	−3.237***	−3.423***
	(0.169)	(0.202)	(0.220)	(0.381)	(0.626)	(0.728)
Observations	9,314	9,314	9,314	9,314	9,314	9,314
Log Likelihood	−258.075	−242.824	−232.798	−220.848	−219.361	−213.642
Akaike Inf. Crit.	520.151	493.648	475.597	453.697	452.722	447.283
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 3: Log-Odds of All Shots Logistic Regression Models

	Dependent variable:					
	goal					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(1)	(2)	(3)	(4)	(5)	(6)
one_timerTRUE	0.776***	0.674***	0.815***	0.648***	0.540**	0.517**
	(0.189)	(0.197)	(0.207)	(0.225)	(0.228)	(0.229)
behind_net_shotTRUE		0.038	−0.029	−0.276	−0.249	−0.227
		(0.284)	(0.285)	(0.300)	(0.301)	(0.303)
through_middle_shotTRUE		0.469***	0.367**	0.705***	0.674***	0.649***
		(0.179)	(0.185)	(0.202)	(0.203)	(0.205)
shot_after_passTRUE			0.512**	0.438*	0.397*	0.404*
			(0.212)	(0.228)	(0.230)	(0.231)
goal_dist				−0.069***	−0.073***	−0.068***
				(0.006)	(0.006)	(0.007)
shot_angle					−0.011***	−0.012***
					(0.004)	(0.004)
period_seconds,						−0.0004*
						(0.0002)
trafficTRUE						−0.309
						(0.209)
advantage						0.104
						(0.157)
Constant	−3.351***	−3.447***	−3.531***	−1.774***	−1.258***	−1.030***
	(0.090)	(0.101)	(0.110)	(0.155)	(0.217)	(0.253)
Observations	4,360	4,360	4,360	4,360	4,360	4,360
Log Likelihood	−704.360	−701.138	−698.431	−610.526	−605.475	−602.828
Akaike Inf. Crit.	1,412.720	1,410.277	1,406.862	1,233.051	1,224.949	1,225.656
Note:						*p<0.1; **p<0.05; ***p<0.01

7.2 Wald Tests

All Events Wald Tests

Model	Res.Df	Df	F	Pr(F)
Model 1	2393	NA	NA	NA
	2394	-1	35.723	0
Model 2	2391	NA	NA	NA
	2394	-3	17.025	0
Model 3	2390	NA	NA	NA
	2394	-4	13.399	0
Model 4	2389	NA	NA	NA
	2394	-5	23.499	0
Model 5	2388	NA	NA	NA
	2394	-6	19.77	0
Model 6	2385	NA	NA	NA
	2394	-9	13.525	0

House Events Wald Tests

Model	Res.Df	Df	F	Pr(¿F)
Model 1	1485	NA	NA	NA
	1486	-1	10.764	0.001
Model 2	1483	NA	NA	NA
	1486	-3	4.877	0.002
Model 3	1482	NA	NA	NA
	1486	-4	3.663	0.006
Model 4	1481	NA	NA	NA
	1486	-5	14.365	0
Model 5	1480	NA	NA	NA
	1486	-6	12.071	0
Model 6	1477	NA	NA	NA
	1486	-9	8.608	0

Non-House Events Wald Tests

Model	Res.Df	Df	F	Pr(¿F)
Model 1	2679	NA	NA	NA
	2680	-1	0.98	0.322
Model 2	2677	NA	NA	NA
	2680	-3	3.134	0.025
Model 3	2676	NA	NA	NA
	2680	-4	4.319	0.002
Model 4	2675	NA	NA	NA
	2680	-5	7.142	0
Model 5	2674	NA	NA	NA
	2680	-6	6.262	0
Model 6	2671	NA	NA	NA
	2680	-9	4.777	0

7.3 Likelihood Ratio Tests

All Events Likelihood Ratio Tests

Model 1

#Df	LogLik	Df	Chisq	Pr(Chisq)
2	-685.820	NA	NA	NA
1	-694.516	-1	17.392	0

Model 2

#Df	LogLik	Df	Chisq	Pr(Chisq)
4	-682.983	NA	NA	NA
1	-694.516	-3	23.066	0

Model 3

#Df	LogLik	Df	Chisq	Pr(Chisq)
5	-680.559	NA	NA	NA
1	-694.516	-4	27.913	0

Model 4

#Df	LogLik	Df	Chisq	Pr(Chisq)
6	-591.300	NA	NA	NA
1	-694.516	-5	206.431	0

Model 5

#Df	LogLik	Df	Chisq	Pr(Chisq)
7	-586.954	NA	NA	NA
1	-694.516	-6	215.124	0

Model 6

#Df	LogLik	Df	Chisq	Pr(Chisq)
10	-583.833	NA	NA	NA
1	-694.516	-9	221.366	0

House Events Likelihood Ratio Tests

Model 1

#Df	LogLik	Df	Chisq	Pr(Chisq)
2	-421.824	NA	NA	NA
1	-426.725	-1	9.802	0.002

Model 2

#Df	LogLik	Df	Chisq	Pr(Chisq)
4	-420.017	NA	NA	NA
1	-426.725	-3	13.416	0.004

Model 3

#Df	LogLik	Df	Chisq	Pr(Chisq)
5	-419.982	NA	NA	NA
1	-426.725	-4	13.486	0.009

Model 4

#Df	LogLik	Df	Chisq	Pr(Chisq)
6	-383.410	NA	NA	NA
1	-426.725	-5	86.629	0

Model 5

#Df	LogLik	Df	Chisq	Pr(Chisq)
7	-383.227	NA	NA	NA
1	-426.725	-6	86.996	0

Model 6

#Df	LogLik	Df	Chisq	Pr(Chisq)
10	-380.030	NA	NA	NA
1	-426.725	-9	93.39	0

Non-House Events Likelihood Ratio Tests

Model 1

#Df	LogLik	Df	Chisq	Pr(Chisq)
2	-211.637	NA	NA	NA
1	-212.080	-1	0.886	0.347

Model 2

#Df	LogLik	Df	Chisq	Pr(Chisq)
4	-207.531	NA	NA	NA
1	-212.080	-3	9.099	0.028

Model 3

#Df	LogLik	Df	Chisq	Pr(Chisq)
5	-203.982	NA	NA	NA
1	-212.080	-4	16.196	0.003

Model 4

#Df	LogLik	Df	Chisq	Pr(Chisq)
6	-193.502	NA	NA	NA
1	-212.080	-5	37.155	0

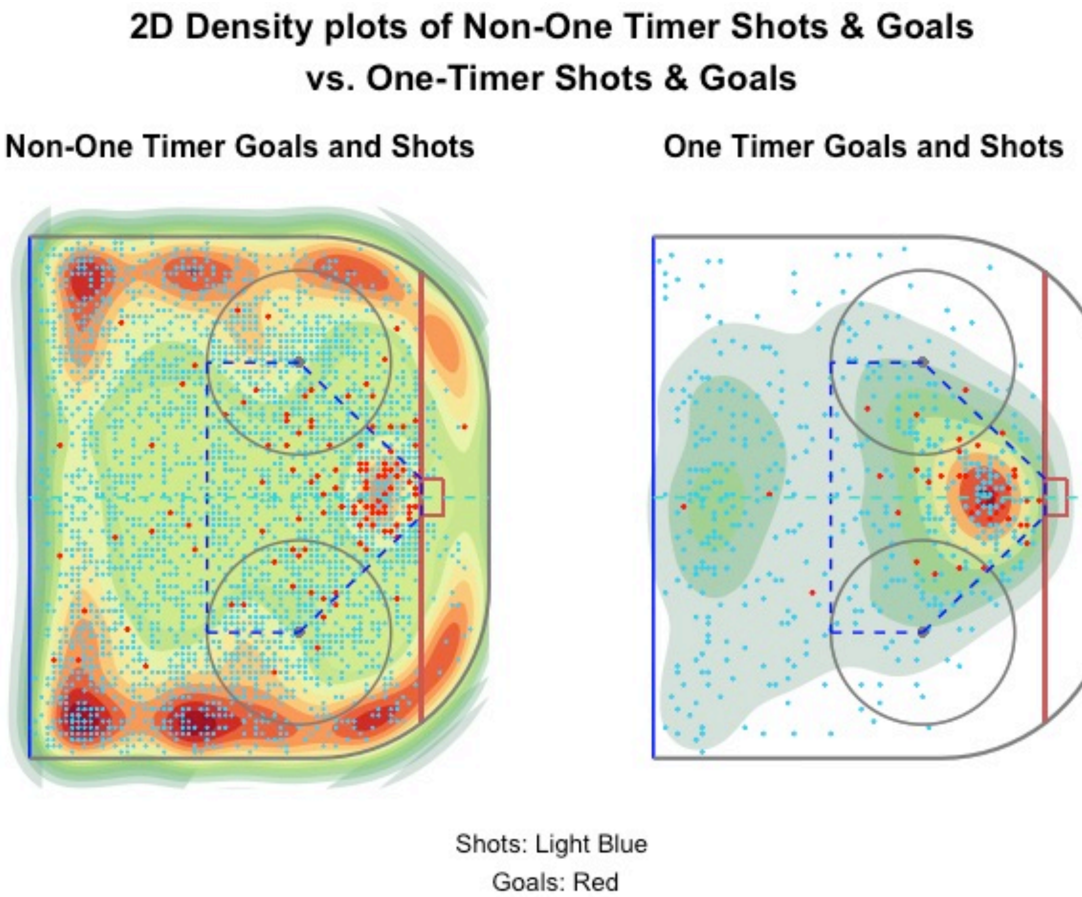
Model 5

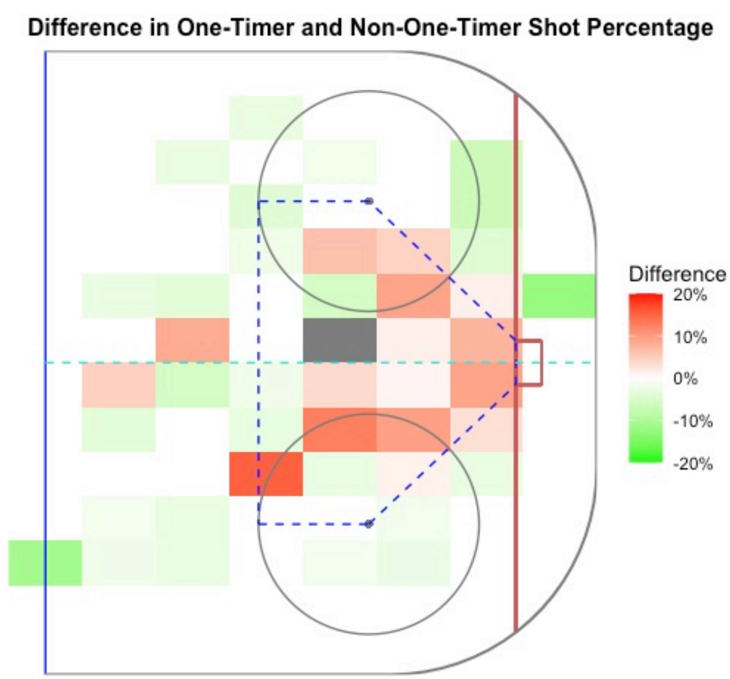
#Df	LogLik	Df	Chisq	Pr(Chisq)
7	-191.244	NA	NA	NA
1	-212.080	-6	41.672	0

Model 6

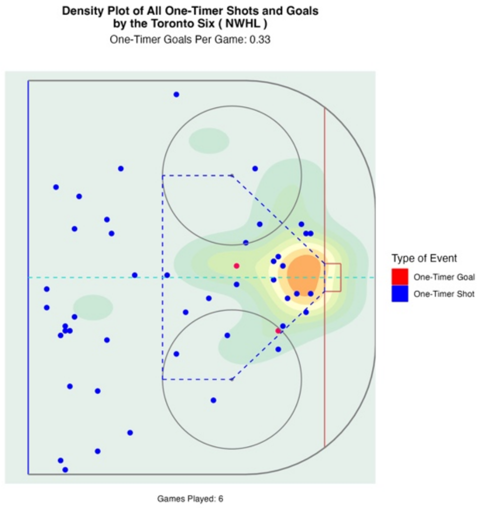
#Df	LogLik	Df	Chisq	Pr(Chisq)
10	-188.824	NA	NA	NA
1	-212.080	-9	46.511	0

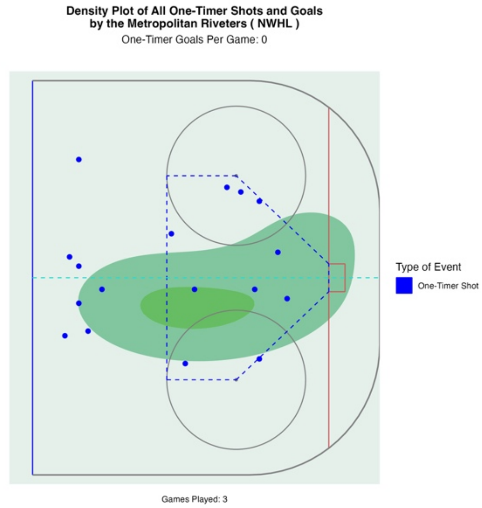
7.4 Plots of Differences in One-Timers by location

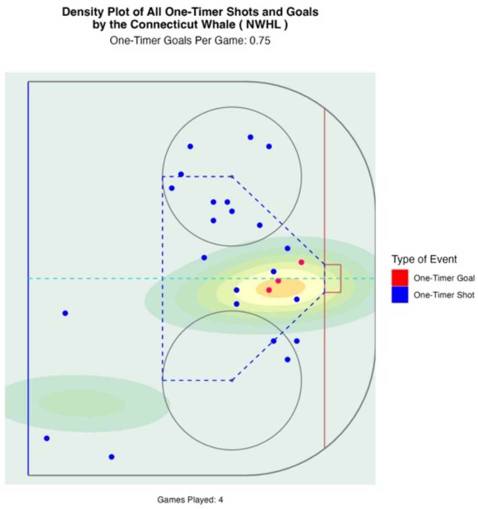


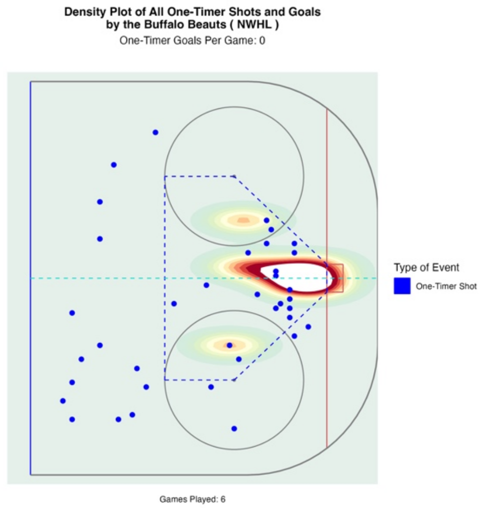


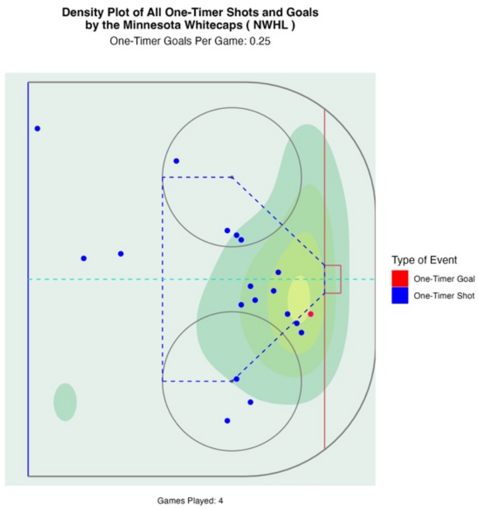
7.5 Plots of One-Timer Shots and Goals by Team

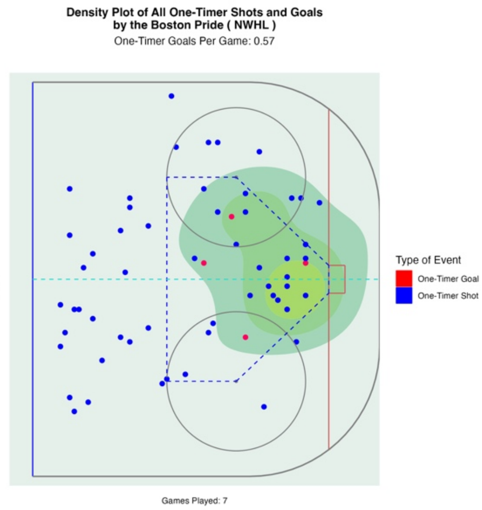


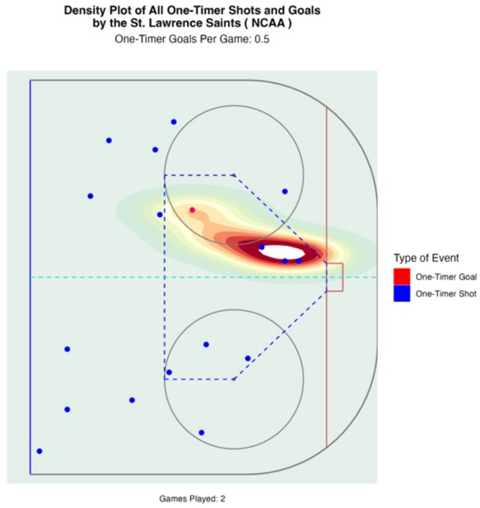


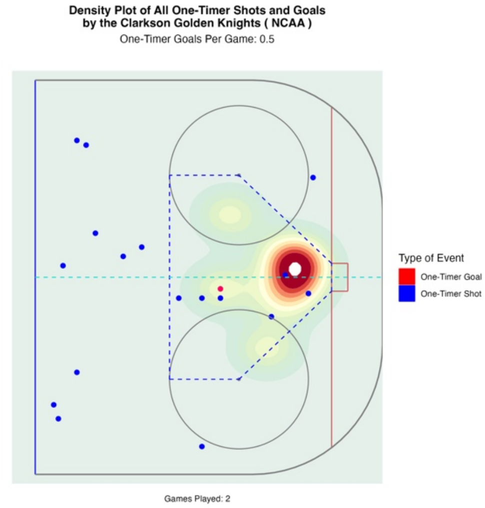


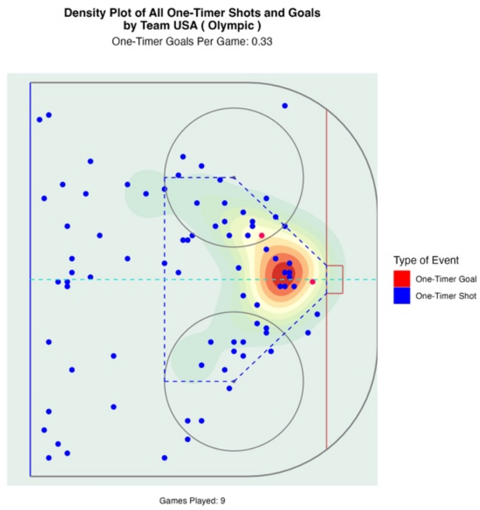


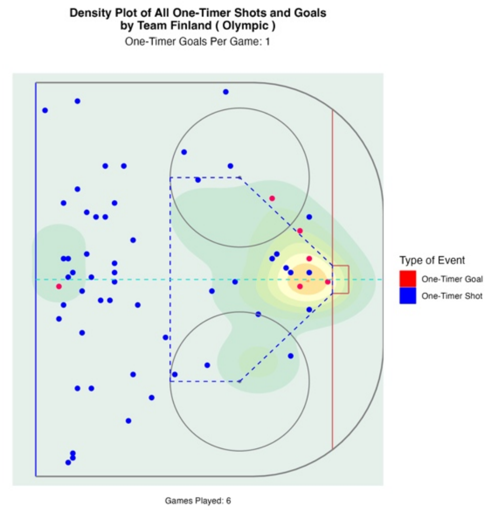


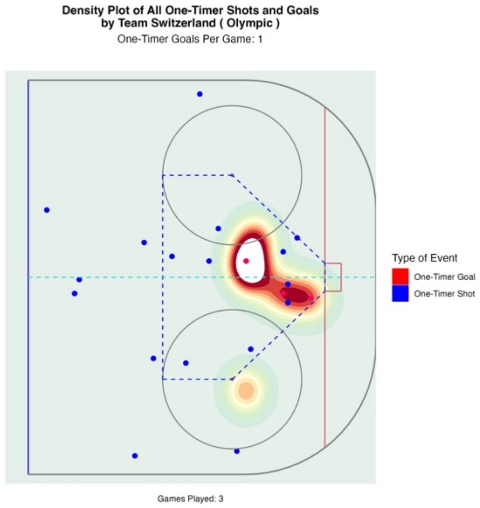


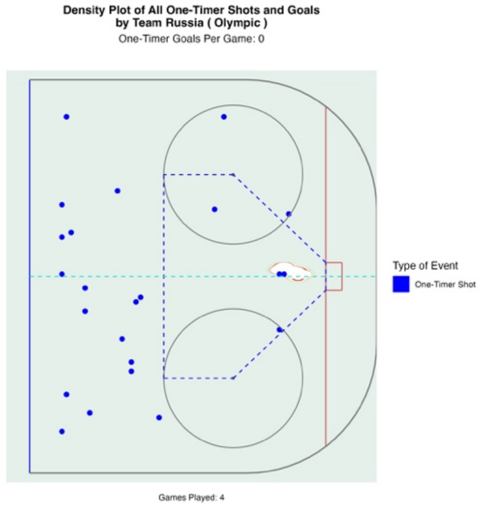

Density Plot of All One-Timer Shots and Goals
by the St. Lawrence Saints (NCAA)
One-Timer Goals Per Game: 0.5
Type of Event
One-Timer Goal
One-Timer Shot
Games Played: 2

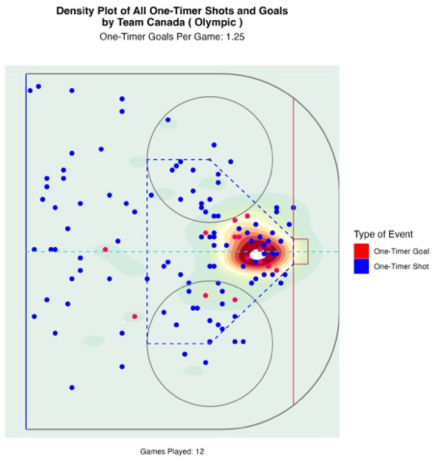

Density Plot of All One-Timer Shots and Goals
by the Clarkson Golden Knights (NCAA)
One-Timer Goals Per Game: 0.5
Type of Event
One-Timer Goal
One-Timer Shot
Games Played: 2


Density Plot of All One-Timer Shots and Goals
by Team USA (Olympic)
One-Timer Goals Per Game: 0.33
Type of Event
One-Timer Goal
One-Timer Shot
Games Played: 9


Density Plot of All One-Timer Shots and Goals
by Team Finland (Olympic)
One-Timer Goals Per Game: 1
Type of Event
One-Timer Goal
One-Timer Shot
Games Played: 6


Density Plot of All One-Timer Shots and Goals
by Team Switzerland (Olympic)
One-Timer Goals Per Game: 1
Type of Event
One-Timer Goal
One-Timer Shot
Games Played: 3


Density Plot of All One-Timer Shots and Goals
by Team Russia (Olympic)
One-Timer Goals Per Game: 0
Type of Event
One-Timer Shot
Games Played: 4


Density Plot of All One-Timer Shots and Goals
by Team Canada (Olympic)
One-Timer Goals Per Game: 1.25
Type of Event
One-Timer Goal
One-Timer Shot
Games Played: 12