4-11-2022

Testing Efficiency in NHL Betting Markets

Charles Luxton
cluxton1@lion.lmu.edu

Joshua Spizman
Loyola Marymount University, joshua.spizman@lmu.edu

David Moore
Loyola Marymount University, David.Moore@lmu.edu

Testing Efficiency in NHL Betting Markets

A thesis submitted in partial satisfaction

of the requirements of the University Honors Program

of Loyola Marymount University

by

Charles Luxton

April 11, 2022

Testing Efficiency in Sports Betting Markets

Charles Luxton; Mentors Joshua Spizman & Dr. David Moore

Abstract

The efficiency of markets is a prominent topic in the field of finance. Market efficiency has been thoroughly examined across many subsectors of finance; however thus far, existing research has sparsely covered the increasingly prominent sports betting market. This market is currently valued at roughly $10B per year (Grandview). In this article, we evaluate the efficiency of sports betting markets, using NHL betting lines and results from 2015-2020 to create a multivariate probit model which tests the market's efficiency. Using a multivariate probit model to identify NHL money line bets with a relatively high probability of success compared to their implied probability, we generate significant profit and beat betting markets, generating an 8.5% ROI when tested against the 20-21 NHL season.

Background

Sports betting has long been an important industry in the United States and worldwide. After a 2018 Supreme Court case ended the prohibition on state legalization of sports betting, the floodgates opened for a rapidly growing industry to continue its upward trajectory, and to veer away from illegal betting markets that have long dominated the U.S. sports betting landscape outside of the formerly singular legalized sports betting market in Las Vegas. As of March 2022, 20 U.S. states have legalized sports betting in some form since the landmark Supreme Court decision, with many more likely to follow.

There are a wide range of different sports betting options such as points spreads, where bettors bet against a team's expected margin of victory, and prop bets, which are based on statistical outcomes within games or a section of a game rather than the overall result. There are also over/under bets, which involve a bet on the total number of points scored in a game. As a means of examining market efficiency and biases within this article, we look strictly at money line betting strategies, which are the simplest form of sports bet. Money line is a pure bet on which team will win a particular game with two binary outcomes. This bet is made against a team's odds of winning as assigned by a given oddsmaker or sportsbook that the bet is placed with.

From a bookmaker's perspective, the process of creating odds (lines) for a given game begins with a bookmaker deciding to open the first line. Once a first line on a game is open, bettors will likely begin betting on the side where they see value. This early stage mainly attracts professional bettors whose bets have a lower maximum limit while the lines may move and be more volatile (Metcalf). Other sportsbooks may also choose to open lines as time passes, with these lines often being close to the initial opening line to protect against arbitrage betting. Arbitrage betting occurs when bettors place bets on opposite outcomes with different sportsbooks which have disparities in their lines so as to guarantee a profit regardless of a game's outcome. Given the emergence of live lines and heavy use of information technology in odds making and betting markets overall, arbitrage betting opportunities are now exceedingly rare, and odds generally line up closely across different sportsbooks. Assuming oddsmakers do not want to take a position on a game's outcome one way or the other, lines will continue to move as the book takes in money. By adjusting lines as bets come in, sportsbooks attempt to bring their money line to an equilibrium where they are guaranteed profit. If bets roll in early on Team A, for example, the line will move to favor the opposing team to incentivize betting on Team B, which will even the equilibrium of where bets have come in. Most of the line movement occurs in the first few hours after opening. In a world of pure theory, bettors whose primary focus is their financial success in gambling markets would use all publicly available information to inform their bets, and these competing forces would align to bring the money line to an 'efficient' end place—one that reflects a fair market price given public information. Gray's (1997) paper on NFL betting explains that, following this logic, if a model based on public information can consistently beat money line odds, there is potential to identify inefficiency in the way bettors and/or sportsbooks shape betting markets through their behavior.

One thing to keep in mind while considering any analysis of sport betting markets is that viewing them through the same lens as we view financial markets is inherently imperfect. Prominent economist Steven Levitt (2004) conducted analysis which found that bookmakers are better at predicting game outcomes than the typical bettor. As a result, books can set lines that can increase profits to an even greater extent than the average premium that they charge bettors. If bookmakers acted like traditional markets and tried to equilibrate supply and demand, they would be less profitable. The encouraging piece of this article for profit-hungry bettors is Levitt's note that this market distortion does create profit opportunities for the most skilled bettors who can identify these biases and exploit them by placing the right bets. To any bettor or individual that thinks they may have what it takes, this market distortion is an inviting opportunity to try and devise a technique to identify betting value. We attempt this in our article.

Literature Review

Any sportsbook or oddsmaker will charge all bettors a premium (vig/vigorish) to place their bets, effectively making it a cost of trading. This means that the summed implied winning probability against a money line for any two teams in a game will inevitably exceed 100%. Oddsmakers are generally taking between a 2% and 5% premium across the four major U.S. sports. Kohers (2013) examines NFL and NCAA market efficiency and quantifies this estimate by asserting that a bettor will have to be right roughly 52.38% of the time against a money line to break even assuming level bets across all games. This estimate holds true across the NHL, MLB, and NBA.

This inevitable challenge of overcoming premiums within sports betting as a bettor raises the bar even higher for anyone trying to create an empirical approach will lead to reliably profitable bets. Some academics argue that bettors themselves are also fine with market inefficiency and bias, and in fact have a hand in helping to create it. When looking at the determinants of sports betting volume within the NBA and NHL specifically, Rodney (2010) contends that bettors make decisions like fans rather than making decisions to optimize financial returns. Using data about betting volume, the article concludes that bettors favor fan-oriented metrics such as evenly matched games and games that appear on national TV as drivers for betting volume rather than financial opportunity or odds with perceived value. This evidence suggests that sports betting is perhaps more about consumption of entertainment than it is a gamble for financial return. Bettors basing their behavior on consumption of entertainment rather than evidentiary reasoning does help further the hypothesis that there is bias in betting markets, on the bettors' side at least, and suggests that these inefficiencies could be a foundation for building a model that is reliably profitable.

The question of whether and how sports betting markets are biased or inefficient was first examined in depth by Golec and Tamarkin (1991), who used regression models and a data set of 15-years of NFL spreads and results to test football betting markets for inefficiencies. The paper concluded that NFL bettors systematically underestimated the relative strength of underdogs and home teams across their NFL data set. Although the magnitude of these biases was relatively small, they were large enough that bettors could profitably exploit these inefficiencies if paying Las-Vegas-like premiums (vig) to place their bets, which at the time were among the lowest offered.

Another attempt to identify market inefficiency by looking for biases and profitable betting strategies in sports betting markets was conducted by Fabrizio (2012). Fabrizio's hypothesis asserted that the more disparity in betting volume between two teams in a matchup, the better a bet on the low-volume team would be. Through his analysis on the NFL and MLB, Fabrizio identified an ROI of 3-6% by following this strategy betting on the low-volume team in cases where one team had less than 20% of betting volume. These returns do not compensate for sportsbook premiums, though the authors refer to them as robust.

Other research in the field has contested the assertion that there is any inefficiency to capitalize on in sports betting markets and has argued it is not possible for bettors to beat random chance regardless of their perceived sports knowledge or advanced information. Cantinotti (2004) conducted a season-long study comparing a group of selected bettors' financial betting returns against random chance for NHL games against the money line. The authors selected participants based on a questionnaire assessing familiarity with sports betting, and selected bettors who claimed to rely on advanced sports knowledge and use extensive public information to drive their betting decision making. The results of this article found that bettors did not achieve a statistically significant level of profitability over the break-even point given premiums (2004).

The dynamics of market efficiency have also been examined differently for alternative sports bet types such as in-game bets, which are increasingly prominent given the betting market's move towards real-time online applications. By comparing in-game bet price opening to their closing lines and outcomes, and analyzing price movement using a logarithmic model, Debnath's (2004) article argues that prices approach the correct outcome as betting volume grows. The article reaches the same conclusion for in-game prop bets, aligning with what we would consider 'efficient market assumptions.' This analysis of in-game bets also suggests that bettors rapidly react to, and apply, public information that can influence betting outcomes. The way that bettors digest information is clearly illustrated in Debnath's comparison of betting behavior in NBA vs. European Soccer markets within this article. In-game bets for the NBA, where new scoring information (scored baskets) occur every 30 seconds or so, have much more marginal pricing movement over time than soccer does, where major scoring information (goals) sometimes only occurs once or twice in an entire game, and pricing movements after these rare events are rapid and sudden. Debnath proved that information is incorporated into betting market prices at the speed which it occurs. This sentiment can be applied to our understanding of bettor behavior for single-game bets as well—which is to say that when information is available, bettors seem to consider it in their decision making. In a vacuum, an increase in information usage while making betting decisions would correspond with greater market efficiency. That efficiency premise is the same as what academics assume about large financial markets, which is the assertion that markets incorporate all public information in their organic pricing of a given asset.

The most significant piece of related research to our article's approach, specifically testing betting results against a probit model, is Gray's (1997) paper on market efficiency in the NFL. In the article, Gray aimed to test the efficiency of NFL betting markets by using a probit model to identify bets on NFL games with a relatively high probability of success. Gray's article used a probit model with five parameters (home win percentage, away win percentage, times home team has beaten spread in last four games, time away team has beaten spread in last four games, and a binary variable indicating if a team is the favorite or underdog) to generate recommended bets against a game's spread. The article outlined the odds of a successful betting outcome based on the model, and Gray demonstrated their findings in categories assigned by the model's probabilistic output. Overall, Gray's probit model correctly predicted 54.56% of NFL outcomes against the spread over a large sample size, suggesting that the NFL market at the time of publication had enough inefficiency to bet profitably using the article's model. In this article, we use a similar methodology to create a probit model for betting on NHL games.

Methods

For this article we used a data set which averaged betting odds across 3 reputable sportsbooks[1] for each game across each of the four major sports over the past five years. Our data set was created to include sourced betting odds for every game along with a range of other information including result, goals, opponent, line movement, home or away status, game date, and more. From this initial information, we also derived implied probability, plus/minus, team record, last game outcome, and other variables as options we could use to create and test probit models for our analysis.

[1] The sportsbooks making up our data set odds averages are: BetOnline, Bovada, Pinnacle Sports

We begin our analysis by examining how bettors would have fared over our sample size by choosing bets using a binary strategy, or the combination of two binary strategies. Some existing research, such as Woodland (2001) argued that some binary strategies such as betting consistently on underdogs or home teams were more likely to succeed than betting randomly or by other criteria, though the article conceded that the margin of success was not enough to compensate for an average bettor's premium. Woodland's data showed that the two-variable combination of Road-Underdog specifically returned over 11% profits for NHL bettors over their chosen time period. As shown in Figure 2, our findings did not bear out this argument, which could likely be explained by improvements in odds making in the past two decades since Woodland's work was published, or by some combination of random chance and our limited sample size.

For example, no combination of Home/Away status paired with Favorite/Underdog status was consistently profitable over the sample period examined in any of the four major sports. This is consistent with historic research including Gray's (1997) which concluded that all variables that they tested individually at the time failed to create consistent profitability year-to-year. For these and all below calculations, we assumed a $1000 unit size for any selected bet based on chosen criteria, consistent with a significant bet that would be in line with that of a professional bettor who may use quantitative techniques to increase betting profitability, as we aim to do in this article.

Sum of $1000 Unit Bet Return - NHL, NBA, NFL, MLB						
	16-17	**17-18**	**18-19**	**19-20**	**20-21**	**Grand Total**
Even	$ (4,377)	$ (4,074)	$ (5,667)	$ (4,009)	$ (3,818)	$ (21,944)
Favorite	$ (176,640)	$ (154,247)	$ (186,109)	$ (144,089)	$ (80,058)	$ (741,143)
Underdog	$ (113,405)	$ (226,006)	$ (47,694)	$ 40,946	$ (143,282)	$ (489,441)
Grand Total	**$ (294,422)**	**$ (384,327)**	**$ (239,470)**	**$ (107,152)**	**$ (227,158)**	**$ (1,252,529)**

Figure 1: This table shows the betting returns for the past five years for the four major sports leagues assuming a bettor's application of a one-variable selection strategy with each of Even, Favorite, and Underdog status.

Sum of $1000 Unit Bet Return - NHL						
	16-17	**17-18**	**18-19**	**19-20**	**20-21**	**Grand Total**
Home - Even	$ (1,000)		$ (857)	$ (4,619)	$ (3,238)	$ (9,714)
Home - Favorite	$ (15,099)	$ (19,903)	$ (53,072)	$ (44,538)	$ 10,771	$ (121,841)
Home - Underdog	$ (15,057)	$ (21,729)	$ (13,744)	$ 9,893	$ (11,319)	$ (51,956)
Visitor - Even	$ 909		$ (857)	$ 3,190	$ 2,619	$ 5,861
Visitor - Favorite	$ (13,069)	$ (6,634)	$ (5,856)	$ (15,089)	$ (3,307)	$ (43,955)
Visitor - Underdog	$ (64,656)	$ (62,931)	$ 30,815	$ 17,313	$ (58,515)	$ (137,973)
Grand Total	**$ (107,972)**	**$ (111,197)**	**$ (43,571)**	**$ (33,850)**	**$ (62,990)**	**$ (359,578)**

Figure 2: This table shows the betting returns for the past five years for the NHL assuming a bettor's application of a two-variable selection strategy across Home/Away and Favorite/Underdog criteria.

Sum of $1000 Unit Bet Return - MLB						
	16-17	**17-18**	**18-19**	**19-20**	**20-21**	**Grand Total**
Home - Even	$ (1,143)	$ (333)	$ (5,857)	$ 4,571	$ 286	$ (2,476)
Home - Favorite	$ (35,894)	$ (68,308)	$ (24,137)	$ 8,412	$ 5,701	$ (114,227)
Home - Underdog	$ (206)	$ (26,760)	$ (44,576)	$ 20,798	$ 3,886	$ (46,858)
Visitor - Even	$ (1,143)	$ (2,286)	$ 3,905	$ (5,190)	$ (1,667)	$ (6,381)
Visitor - Favorite	$ (40,774)	$ (15,629)	$ 2,319	$ (25,538)	$ (26,499)	$ (106,120)
Visitor - Underdog	$ (49,986)	$ 211	$ (45,554)	$ (26,945)	$ (63,880)	$ (186,154)
Grand Total	**$ (129,146)**	**$ (113,104)**	**$ (113,900)**	**$ (28,102)**	**$ (82,174)**	**$ (466,426)**

Figure 3: This table shows the betting returns for the past five years for the MLB assuming a bettor's application of a two-variable selection strategy across Home/Away and Favorite/Underdog criteria.

Sum of $1000 Unit Bet Return - NFL						
	16-17	**17-18**	**18-19**	**19-20**	**20-21**	**Grand Total**
Home - Even	$ (182)	$ (182)	$ (182)	$ 818	$ 1,818	$ 2,091
Home - Favorite	$ (29)	$ (1,235)	$ (7,482)	$ (19,281)	$ (12,805)	$ (40,831)
Home - Underdog	$ (15,776)	$ (10,158)	$ 12,250	$ (12,698)	$ (23,400)	$ (49,781)
Visitor - Even	$ (182)	$ (182)	$ (182)	$ (1,091)	$ (2,000)	$ (3,636)
Visitor - Favorite	$ (4,725)	$ (1,038)	$ (10,457)	$ (3,118)	$ 4,439	$ (14,899)
Visitor - Underdog	$ (17,400)	$ (24,735)	$ (5,520)	$ 25,075	$ 5,560	$ (17,021)
Grand Total	**$ (38,933)**	**$ (36,830)**	**$ (11,832)**	**$ (10,757)**	**$ (25,988)**	**$ (124,339)**

Figure 4: This table shows the betting returns for the past five years for the NFL assuming a bettor's application of a two-variable selection strategy across Home/Away and Favorite/Underdog criteria.

Sum of $1000 Unit Bet Return - NBA						
	16-17	17-18	18-19	19-20	20-21	Grand Total
Home - Even	$ 3,000	$ (2,455)	$ 1,091	$ (3,636)	$ (2,727)	$ (4,727)
Home - Favorite	$ (50,694)	$ (19,903)	$ (44,466)	$ (45,826)	$ (28,154)	$ (189,044)
Home - Underdog	$ 19,824	$ (25,578)	$ 15,041	$ (23,230)	$ 31,724	$ 17,781
Visitor - Even	$ (4,636)	$ 1,364	$ (2,727)	$ 2,091	$ 1,091	$ (2,818)
Visitor - Favorite	$ (17,715)	$ (21,367)	$ (43,802)	$ (5,261)	$ (29,204)	$ (117,349)
Visitor - Underdog	$ 31,850	$ (55,026)	$ 5,392	$ 41,419	$ (28,736)	$ (5,100)
Grand Total	**$ (18,371)**	**$ (123,196)**	**$ (70,168)**	**$ (34,444)**	**$ (56,006)**	**$ (302,185)**

Figure 5: This table shows the betting returns for the past five years for the NBA assuming a bettor's application of a two-variable selection strategy across Home/Away and Favorite/Underdog criteria.

Based on past research and data from Figures 1-5, simplistic single-and dual- variable betting approaches do not indicate market inefficiency or indications of a consistently profitably approach. To further examine market efficiency, we create a probit model using NHL data from 2016-2020 and test that model on 2021 game results to assess its ability to generate statistically significant profit. To build this probit model, we used eight variables. The variables are whether a team is coming off a back-to-back (B2B), whether a team is coming off a win or loss (LGB), whether a team is a favorite or underdog (FUB), whether a team is at home or away (HVB), how many rest days a team has had (RD), a team's win percentage (WP), a team's plus-minus (PM), and the game odds' premium/vig (VIG). We use B2B, LGB, FUB, RD and HVB to capture binary or continuous conditions that can impact a game's outcome. WP and PM are used to attempt to quantify a team's quality at a single-game event level on a rolling basis, resetting each season. We hypothesize that more uncertainty about a game's outcome could help to identify profitable betting opportunities. VIG proxies for this uncertainty.

Findings

Based on our data set from the 2016-2020 NHL seasons, we estimate the following probit model using 12,128 observations. Each variable's coefficient parameter is listed below, along with the standard error listed in italics. The model was created in Stata with no constant.

$$Y_i = b_1B2B + b_2LGB + b_3FUB + b_4HVB + b_5RD + b_6WP + b_7PM + b_8VIG$$

Parameter	Estimate
b_1	-0.092
	0.035
b_2	-0.014
	0.024
b_3	0.348
	0.274
b_4	0.082
	0.026
b_5	-0.027
	0.010
b_6	-0.104
	0.042
b_7	0.003
	0.001
b_8	-1.209
	1.143

Figure 6: This table shows each variable's coefficient parameter within our NHL probit model based off data from the 2016-2020 NHL seasons. The standard error for each parameter is listed below in italics.

Of the eight variables, six of them are statistically significant in predicting game outcomes on a binary win-loss scale. The only two variables which are not statistically significant are last game result, and premium (vig). The fact that last game result is not statistically significant seems to suggest that 'momentum' on a single game scale is not something that should be considered in building betting models or making betting decisions, though more research would be needed to determine this definitively.

To assess our ability to identify market inefficiency by generating profits, we applied our model, which was based on 2016-2020 NHL game data, to the 20-21 NHL season. We generated a so-called ‘confidence score’ for each team in each game, with a negative score being the model’s indication of a ‘bad bet,’ and a positive score being an indication of a good betting candidate. When applied, these confidence scores ranged from a minimum of -1.300 to a maximum of 1.482. Using the coefficients generated from existing data and applied to the 20-21 season, we assessed the model by creating confidence level categories and assessing the payout, betting units +/-, and ROI % for the model’s recommended bets in view of each category restriction. The model output for the 20-21 season gave us the following results with an assumed unit size of $1000.

Probit Model Index	Bets Placed (Units)	Payout	+/- Units	ROI %
No Model Application (All Games)	1831	$ (59,664)	-60	-3.3%
0 < Index	1314	$ (10,418)	-10	-0.8%
0.5 < Index	915	$ (5,751)	-6	-0.6%
1 < Index	506	$ 13,226	13	2.6%
1.25 < Index	249	$ 21,045	21	8.5%

Figure 7: This table shows the betting results for our NHL probit model as applied to the 20-21 NHL season with selected confidence score categories. Assumed unit size is $1000.

The results from testing the model on the 20-21 season look encouraging. As expected, betting on every team in every game without applying any criteria generates the most negative result, coming in at a -3.3% ROI. This result is consistent with what we would expect given the established range of 2-5% premiums that bettors expect to see on NHL games. Since the model's confidence score outputs ranged from a minimum of -1.300 to a maximum of 1.482, we established four benchmarks for assessment at the 0, 0.5, 1, and 1.25 level. An increase in the confidence score should coincide with what the model considers to be a better and better bet given the data it is fed. Therefore, a linear increase in ROI % would be expected as the confidence score cutoff increases. This is the result we see, with the model breaking even on ROI % somewhere between the 0.5 and 1.0 confidence score cutoffs. The model also gets pickier as the confidence score increases, with the model picking 249 out of a possible 1831 bets as good candidates at the 1.25+ confidence score level. The strong 8.5% after cost of trading, which means it factors in premiums, ROI at that highest cutoff suggests that the highest confidence score cutoff does indeed identify the best betting candidates through a more selective approach. This is advantageous to application for betting because it would require a lower initial capital investment for bettors to make healthy returns. After replicating a similar index level testing with data from 2016-19 against 2019-20 using the same formula, a similar ROI % was achieved, on pace for 7.7% if the season had reached 82 games.

Given the model was only applied to a singular season for testing, it is difficult to take these results as being fully conclusive about market inefficiency. To further reinforce our thesis and the validity of the model, it will ideally continue to be tested against results in future season publicly in real time. Another complicating factor with testing against the 20-21 season is the potential impact of the COVID-19 pandemic. Several teams, most prominently the Vancouver Canucks, went through extended stretches missing players due to COVID protocols, which likely influenced their game performance and would therefore interfere with assumptions about efficient betting. It is also potentially problematic that our model variables were tested against non-COVID games but then were subsequently applied to games during a season impacted by COVID. This is especially the case when considering variables such as home/away status that were likely materially affected by COVID impacts such as empty stadiums. Teams also had their schedules shifted to play opponents several times in a row far more often than a normal season, which could have distorted variables such as last game status, back-to-back status, and rest days.

An important part of identifying profitable betting strategies is knowing the benchmark against which bettors must perform in order to break even. As noted earlier, existing research estimated the average premium to be around 2.5% across the four major sports. Historically, hockey has been viewed as a slightly higher-premium sport than the other four major sports due to lower betting volume leading to exposure to unbalanced betting. Our analysis of NHL premiums identified a steep decrease in average vig between the 2017-18 and 2018-19 season. Past premiums appeared to sit right around 3.8%, but premiums have sat closer to 2.3% over the past three years according to our analysis as displayed below. There is no established cause for this drop-off, but one likely factor could be new entrants into the market of sports betting websites and books creating competition for users and driving down premiums. Regardless, the impact is very clear and consistent over our sample.

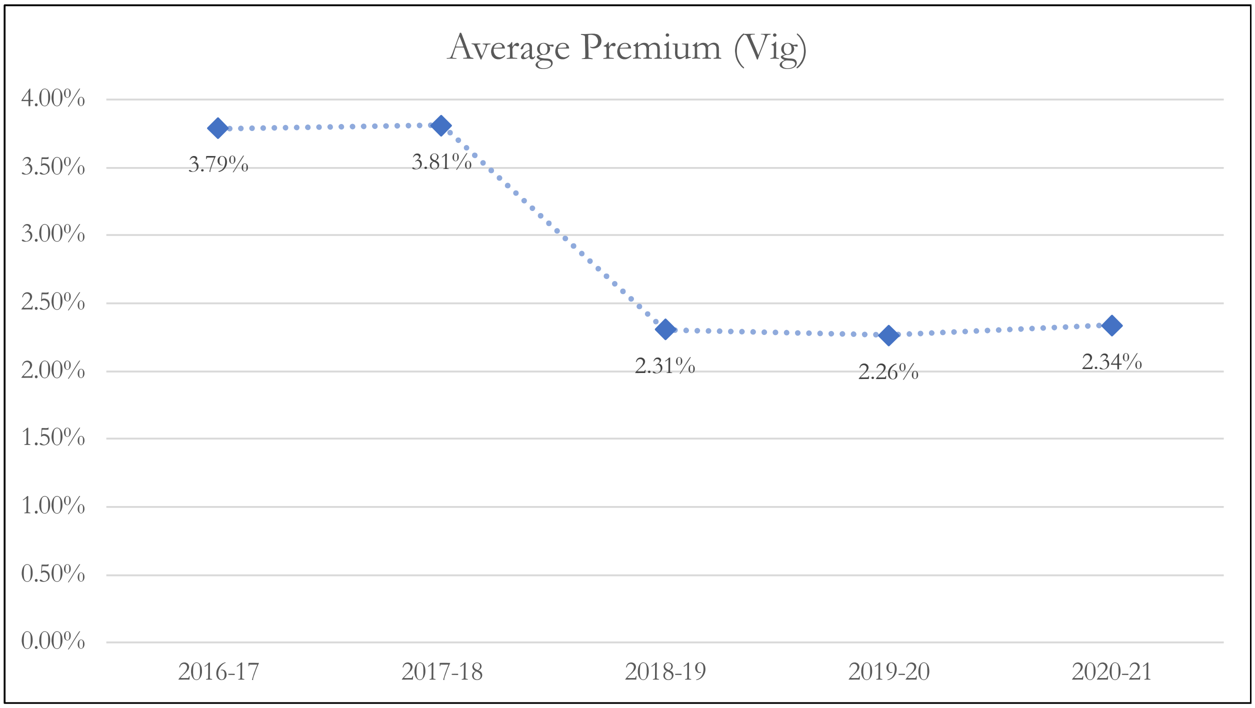

Figure 8: This table shows the average oddsmakers premium to place a bet on an NHL money line over each of the past five years.

Our model's 8.5% ROI provides a healthy margin for profitability and potential to beat the market. Preliminarily, we can take this to be a demonstration of market inefficiency in NHL betting markets since the model is based on publicly available information that bettors could apply to their analysis in placing bets, or that bookmakers could apply in setting lines, though both have failed to do so thus far. Because money line odds can be moved by bettors or oddsmakers, we can assert that betting markets appeared to be inefficient or biased during the 20-21 season, but this inefficiency could be corrected by market forces, whether it be by oddsmaker or bettor behavior.

Conclusion

Woodland asserted in their 2001 article on NHL betting markets that "The market is said to be inefficient if a strategy exists yielding average returns higher than a strategy based on a random selection of teams" (Woodland). Based on this criterion, our research indicates that there are likely inefficiencies in the NHL betting markets based on the robust profitability demonstrated by our multivariate probit model. At the highest benchmark application, our model was able to identify 249 NHL games to bet on during the 20-21 season for a profit of +21 betting units (8.5% ROI). This finding is limited by the fact that the sample size is based on only four years of data, and the model's ability to predict outcomes has been tested on only one year. To continue our research, we will look to apply the model to future years and judge whether its strong performance is resilient, and whether factors that correlate with predictability in NHL money line performance shift at all year-to-year. Future research could also aim to create a similar probit model for other sports to test inefficiencies and assess potential profitability in other sports betting markets. Another continuation of this project we would potentially like to pursue is the creation of individual team models to further refine the model's ability to identify value in betting candidates.

References

"Sports Betting Market Size & Share Report, 2021-2028." *Sports Betting Market Size & Share Report, 2021-2028*, Grandview Research, Sept. 2021, https://www.grandviewresearch.com/industry-analysis/sports-betting-market-report.

Gray, Philip K., and Stephen F. Gray. "Testing market efficiency: Evidence from the NFL sports betting market." *The Journal of Finance* 52.4 (1997): 1725-1737.

Metcalf, Matt. “How Lines Are Set: An Oddsmakers Perspective.” *Circa Las Vegas*, https://www.circalasvegas.com/blog/sportsbook/from-the-experts/article/how-lines-are-set-an-oddsmakers-perspective/.

Golec, Joseph, and Maurry Tamarkin. "The degree of inefficiency in the football betting market: Statistical tests." *Journal of Financial Economics* 30.2 (1991): 311-323.

Kohers, Gerald, Mark Tuttle, and Donald Bumpass. "EXAMINING NCAA/NFL MARKET EFFICIENCY." *Journal of Economics and Economic Education Research* 14.3 (2013): 67-72. *ProQuest.* Web. 7 Dec. 2021.

Paul, Rodney J., and Andrew P. Weinbach. "The determinants of betting volume for sports in North America: Evidence of sports betting as consumption in the NBA and NHL." *International Journal of Sport Finance* 5.2 (2010): 128.

Woodland, Linda M., and Bill M. Woodland. “Market Efficiency and Profitable Wagering in the National Hockey League: Can Bettors Score on Longshots?” *Southern Economic Journal*, vol. 67, no. 4, Southern Economic Association, 2001, pp. 983–95, https://doi.org/10.2307/1061582.

Fabrizio, Dan, and James Cee. "A Contrarian Approach to the Sports Betting Marketplace." *MIT Sloan Sports Analytics Conference (2012), https://www.sportsinsights.com/images/downloads/Sports_Insights_Make_Smarter_Bets.pdf*

Cantinotti, Michael, Robert Ladouceur, and Christian Jacques. "Sports betting: Can gamblers beat randomness?." *Psychology of addictive behaviors* 18.2 (2004): 143.

Debnath, Sandip, et al. "Information incorporation in online in-game sports betting markets." *Proceedings of the 4th ACM conference on Electronic commerce*. 2003.

Steven D. Levitt, Why are Gambling Markets Organised so Differently from Financial Markets?, *The Economic Journal*, Volume 114, Issue 495, April 2004, Pages 223–246, https://doi.org/10.1111/j.1468-0297.2004.00207.x