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UNIVERSITY OF NORTHERN COLORADO

Greeley, Colorado

The Graduate School

THE NATIONAL HOCKEY LEAGUE TOTALS MARKET: EFFICIENCY, PROFITABILITY, AND HEURISTIC BEHAVIORS

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree of
Doctor of Philosophy

Alexander Traugutt

College of Natural and Health Sciences
School of Sport and Exercise Science
Sport Administration

May 2018

This Dissertation by: Alexander Traugutt

Entitled: *The National Hockey League Totals Market: Efficiency, Profitability, and Heuristic Behaviors*

has been approved as meeting the requirement for the Degree of Doctor of Philosophy in the College of Natural and Health Sciences in the School of Sport and Exercise Science, Program of Sport Administration.

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ABSTRACT

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The National Hockey League (NHL) totals market provides an optimal setting to test the theory of efficient markets. Under the notion of market efficiency, prices of an asset are reflexive of all publicly available information, making it impossible to enjoy consistent, above-average, returns. In contrast to the other major professional sporting leagues in North America, the NHL was the last to become fully integrated into sportsbooks, thus making it more susceptible to inefficiencies. To date, there has only been one published study related to the NHL totals market, which found deviations from market efficiency. The present research builds and expands upon these findings by analyzing a more expansive dataset, which included the closing total and associated odds for each contest. Furthermore, the present work analyzed the efficiency and profitability of the market through five betting strategies, each motivated by common heuristics and decision making biases. Results indicated that the NHL totals market was largely efficient, with only one strategy yielding a marginal above-average return. Thus, the influence of heuristics appeared to be appropriately priced in the market. This is consistent with the central premise of the market efficiency, in that financial markets are efficient with regard to any particular strategy or piece of information over a sustained period of time.

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Most importantly, to my wife, Amanda. Your patience and unwavering support have been instrumental to my success. Ultimately, the love and encouragement that you provided is what made the completion of this dissertation possible. I only hope that I can one day return the favor.

For my father,

GEORGE TRAUGUTT

1947-2017

It was through our relationship that I learned
the true value of education.

This is for you, Dad.

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CHAPTER I

INTRODUCTION

The American people are a "people of chance" (Findlay, 1986, p. 4). Capitalism in America thrives on the common occurrence of individuals taking chances, speculating on uncertain outcomes, and determining the profitability potential of investments. Not surprisingly, these capitalistic activities have shaped the practice of gambling, which has become an integral part of mainstream culture. In fact, the gambling industry has become one of the biggest industries in the United States, in terms of both the amount of revenue generated and the number of active participants (Davies & Abram, 2001). While the exact number of individuals who wager on sports cannot be effectively determined, research estimates that roughly 25 percent of adults in the United States make at least one bet on the outcome of a sporting event each year (Davies & Abram, 2001). This widespread participation, some would argue, has been a driving force behind the popularity of sports in American society.

The examination of sport wagering markets has only recently gained significant academic attention. This lack of prior attention is tied to the negative stigma associated with gambling and a general reluctance to introduce sports gambling into the mainstream scholastic model. Despite this, the enormity of the American sports betting market makes it an ideal candidate for exploration. Studies have estimated that it alone holds the potential to produce $12.4 billion in annual revenue (Purdum, 2015). The American Gaming Association estimated that roughly $90 billion was wagered on football (college and professional) in 2016, with $4.7 billion wagered on Super Bowl 51 (American Gaming Association, 2016, 2017a). For the month-long 2017 March Madness collegiate basketball tournament, an estimated $10.4 billion was wagered by individuals in the United States. Even in the arguably less popular sport of Major League Baseball (MLB), American sports fans wagered close to $37 billon over the course of the 2017 season (American Gaming Association, 2017b). In total, some experts estimate that the worldwide sports wagering industry is worth between $500 billion and $1 trillion dollars (Campbell, 2013). While research has yet to provide similar wagering estimates for the sport of hockey, one can assume that over the course of a season, the National Hockey League (NHL) betting market operates as a multi-billion-dollar enterprise.

The growth of sports betting has spurred a unique line of research pertaining to economic efficiency and profitability (e.g., Gandar, Zuber, & Johnson, 2004; Gandar, Zuber, Johnson, & Dare, 2002). This increase in academic attention has coincided with growth in the size and liquidity of the various sports betting markets, creating new opportunities for empirical research. As the sports wagering industry continues to flourish, findings pertaining to economic inefficiency and profitability become even more pertinent.

Given their parallel nature, many individuals liken investing in the stock market to gambling on the outcome of sporting events. As Grant, Johnston, and Kwon commented, “betting markets are growing rapidly and are no longer distinct, even superficially, from other investment markets” (Grant, Johnstone, & Kwon, 2008, p. 10). Fundamentally, individuals who participate in either domain assume the following: a potential for financial gain or loss with prior research holding the potential to improve one's chances of success. Thus, methods for measuring efficiency in the financial sector are commonly, and appropriately, used in the sports wagering setting.

Despite the obvious parallels, it is important to note inherent differences between the two markets. First, the makeup of sporting contests allows for more simplified testing of market efficiency. In the financial setting, a stock is infinitely lived. This makes the testing of economic efficiency prolonged and cumbersome. Conversely, sporting events feature a definitive start and end that is oftentimes realized in the span of a few hours. Thus, tests of efficiency and profitability can be conducted in a more simplified manner with an abundance of readily available data (Williams, 1999). Second, sports betting is largely more difficult and riskier than investing in stocks. As Randall Fine, managing director of the casino consulting firm The Fine Point Group noted, "a large, steady company has a low chance of plummeting and causing you to lose all your money, but even Peyton Manning doesn't cover the spread sometimes" (as cited in Egan, 2014, para. 11). Nevertheless, many of the strategies used on Wall Street are analogous to the tactics used by sports bettors and thus informed this research.

Utilization of theories and strategies from the financial sector provide a foundation for examining the efficiency of sport wagering markets. The market, however, continues to evolve and self-correct. This makes it difficult to develop strategies that can achieve consistent above average returns. Thus, the information that may be leveraged from analyses of economic inefficiency and profitability is relevant to both academics and members of the public.

Statement of Purpose

The purpose of this research was to analyze the economic efficiency and profitability of the NHL totals market through the use of heuristic-based betting strategies. The strategies analyzed were constructed using common behavioral biases in an effort to provide clearer explanations for any rejections of market efficiency and/or instances of significantly positive returns. The totals market in the NHL is an interesting market to analyze for a variety of reasons. First, the fact that there is no true favorite or underdog makes the testing of traditional biases in their original form invalid, thus creating new opportunities for empirical tests. Second, the NHL totals market has received the least amount of research attention in comparison to other professional sports and even racetrack betting. Lastly, the lack of widespread media attention and low limits placed on the market makes it ripe for inefficiency, as oddsmakers may underinvest in the development of precise prediction models, given the small potential losses that may be incurred from incorrectly setting an over/under line. These points specifically make this market more susceptible to financial inefficiency in ways not present in more popular markets.

In an economically efficient market there is no strategy by which an individual could consistently increase their wealth and utility (Bradfield, 2007). This concept is what drives the Efficient Market Hypothesis (EMH), which is widely regarded as one of the most influential and compelling theories in finance and economics (Fama, 1965; Malkiel, 2012). At its most basic level the EMH posits that prices of an asset fully reflect all publicly available information making it impossible for investors to consistently earn above-average profits (Fama, 1965; Samuelson, 1965). In contrast to its initial application in the financial sector, the EMH has become a commonly applied theory for gauging the economic efficiency of sports wagering markets and thus served as the theoretical foundation of this study.

In order to provide a more comprehensive analysis of this market, tests of market efficiency and profitability were tested against five betting strategies comprised of common behavioral biases. As is the case in securities trading, bettors, like investors, are known to utilize heuristics, or general rules of thumb, to arrive at decisions more quickly without the need for extensive cognitive processing. For this study, the availability and representativeness heuristics were utilized as the basis for strategy formulation. Previous research has found that inefficiencies in sport wagering markets may be most plausibly explained by heuristic behaviors and their influence on the decision making process of investors in situations of risk and uncertainty (L. M. Woodland & B. M. Woodland, 2015).

Sports wagering markets provide an optimal framework to test the theory of efficient markets. The literature concerning this concept in professional sporting leagues is extensive, yet lopsided, with most of the focus having been placed on the point spread market in the NFL. This has left a gap in the literature concerning other markets, and specifically the NHL totals market. Moreover, consistent utilization of heuristics to explain bettor behavior in sports wagering markets has only been empirically investigated by a few very recent studies. Thus, there is a clear opportunity to utilize these concepts and build upon the findings of these recent studies to gain a greater understanding of investor behavior on both a micro and macro level.

Hypotheses

Two separate hypotheses were considered when assessing the efficiency and profitability of the five heuristic-based betting strategies. Consistent with previous research, a two-step approach was utilized in which significance tests of win proportions were first evaluated for market efficiency followed by similar tests for profitability, when appropriate (e.g., Sung & Tainsky, 2014; B. M. Woodland & L. M. Woodland, 2000). Tests of market efficiency were conducted for in the aggregate and for every odds pairing within each strategy based on the following

$$\text{HO1: } \pi = \rho$$

$$\text{H1: } \pi > \rho \text{ or } \pi < \rho$$

where π is the objective win probability and ρ is the subjective win probability of a given contest from the vantage of the under bettor. When a particular odds pairing rejected the null of market efficiency, tests of significance for the profitability of that odds pairing were conducted. Such a test was characterized by the following

$$\text{HO2: } \pi \leq \text{G}$$

$$\text{H2: } \pi > \text{G}$$

where π is the objective win probability and G is the is break-even win proportion needed to achieve profitability. Once appropriate hypotheses tests were conducted for all strategies and odds pairings, the success of each strategy was determined based on actual financial returns.

Rationale

To date, no studies have examined the efficiency of the NHL totals market while simultaneously seeking to identify the role that biases, or heuristics, played in the bettors' decision making process. While some studies have sought to address the economic efficiency of the NHL totals market and assert that their findings supported a particular bias (e.g., favorite-longshot bias), they failed to provide empirically tested conclusions for their assertions. Therefore, a central objective of the current study was to produce more definitive and empirically supported conclusions about the ways in which heuristics can explain market (in)efficiency.

The widespread popularity of sports wagering in the United States has created a scenario where many bettors seek to devise some sort of system or model to systematically profit on game outcomes. The fundamental question of whether the NHL totals market is efficient, in terms of the lines set by the oddsmakers, has significant economic implications for both the sportsbook and the individual bettor as an investor. By focusing on well-known heuristics, more accurate betting strategies were devised and tested that theoretically account for common bettor biases (which may or may not already be accounted for by the bookmakers). This permitted more comprehensive statistical tests to be conducted in an effort to better understand bettor biases and whether their exploitation can lead to significant and consistent returns.

Delimitations

This study examined the efficiency of the NHL totals market and the extent to which common heuristics can explain bettor behavior. The methods for analyzing the data were quantitative in nature and pertained only to the NHL. Given the unique nature of this betting market, results can be generalized, with caution, to totals markets in other leagues or other financial markets. The varying odds structure and the unique nature of this sport were what drove this rationale. Lastly, it is important to note that the function of this research was to recognize existing economic inefficiencies. As such, these findings should not to be taken as an indication of future performance given the variables and scenarios measured.

Limitations

1. This research operated under the assumption that sportsbooks seek to balance their books as opposed to taking a vested position in the market. Such an assumption is consistent with previous research and is necessary to allow for the calculation of subjective probabilities and for accurate conclusions to be drawn. If it was assumed that bookmakers did not operate in a balancing fashion, the statistical tests and subsequent assessments in this study would be considered invalid. While it would be ideal to know precisely how bookmakers operate, such information is not publicly available.
2. This study only considered closing totals and associated odds as opposed to tracking and assessing line movements.
3. The manner in which heuristics were considered and exploited was admittedly simplistic. It was essential to the author, however, that the results be easily interpreted by readers across disciplines. The potential for this information to be incorporated into more advanced models is present.

Definition of Terms

Bettor: An individual who places a bet or wager.

Betting line: A proposition, generally involving two teams, on which an individual can wager. These lines are affixed with odds so that bettors can calculate payouts at the time of wager placement.

Bookmaker or *Oddsmaker:* An individual who calculates odds and sets betting lines; generally operating out of a sportsbook. (The definition of *sportsbook* is provided below.)

Closing line: The final betting line offered by a bookmaker before the start of a contest.

Closing total: The final total line (over and under) offered by a bookmaker before the start of a contest.

Efficient Market Hypothesis: A financial theory that suggests financial markets do not allow investors to earn above-average returns because market prices reflect all publically available information (Fama, 1965; Samuelson, 1965).

Efficiency: (in sports betting) Is determined by examining if returns to the bettor are greater than the commission associated with a given wager (L. M. Woodland & B. M. Woodland, 2015).

Favorite: This side, or total, will always have a negative (-) symbol preceding the odds. As such, bettors will need to wager a higher amount to win $100 in comparison to the underdog.

Heuristics: General rules of thumb that are utilized to reduce the amount of time and effort needed to effectively and efficiently make decisions (Tversky & Kahneman, 1974).

Informed Bettor: Also known as a “wiseguy” or “sharp,” these individuals deal primarily in large figure bets that have the ability to influence the betting market.

Odds: In sports betting, odds are utilized to indicate the probability of a particular event.

Profitability: (in sports betting) Is determined by examining if win percentages exceed calculated break-even win proportions, which account for bookmaker commissions.

Sportsbook: The entity that employs the bookmakers or oddsmakers and pays out winnings.

Totals Line or *Market:* A betting structure in which the total number of goals (points) is the sole determinant of wager outcome.

Underdog: This side, or total, will always have a positive (+) symbol preceding the odds. As such, bettors will need to wager a lower amount to win $100 in comparison to the favorite.

CHAPTER II

REVIEW OF LITERATURE

The review of literature for this study is divided into five sections. The first provides a detailed description of the EMH and the concepts associated with this well-known financial theory. The second segment focuses on two common heuristics; availability and representativeness. Emphasis is placed on description of the biases associated with each construct, as these biases are what make each of these concepts unique. The third section details the basic functions of the sport wagering market, including basic market constructs and the role of bookmakers. Lastly, to bridge the gap between theory and practice, a detailed review of the empirical literature concerned with applications of the EMH and heuristic theories to the various sports wagering markets will be provided. The review will focus on studies of the totals market in each of the four major North American sports, as this market is the primary focus of the present research.

The Efficient Market Hypothesis

The EMH defined by Fama (1965) and Samuelson (1965) posits that financial markets do not allow investors to earn above-average returns because market prices incorporate all publically available information. More specifically, Samuelson (1965) detailed that in an efficient market, price changes should be unforecastable, or unpredictable, if they accurately and appropriately incorporate the information available to all market participants. Similarly, Fama (1970) elaborated that the EMH acts under the assumption that prices fully reflect all publicly available information. Under this notion, a portfolio built on either technical or fundamental analysis would enable an investor to achieve higher returns than one built upon randomly selected holdings, due to the fact that prices fluctuate at random. Any abnormal returns are simply interpreted as an EMH anomaly (Malkiel, 2012).

The Random Walk Hypothesis

The underlying concepts of the EMH are closely tied to the Random Walk Hypothesis (RWH), which refers to the mathematical theory of a random walk. In the stock market, a random walk is used to describe how incremental or short-term changes in prices cannot be predicted by technical analysis because they are completely random. Despite this definition, investors and analysts continue to make assumptions regarding short-term future price movements.

As an illustrative example, consider the following. Envision standing at the midpoint of a line drawn on the ground. Using a fair coin, flip the coin ten times and if comes up heads, take one step to the right, and vice versa for tails. After ten flips, imagine where you may be standing in relation to your original position. Given our instinctive nature and biases, we may assume that our final position will not be far from our starting place, yet the possibility of ending up 10 steps to the left or right is present. Given the assumptions of the RWH, it is not possible to predict the probability of the next flip being heads or tails based on the previous outcome. Rather, these events occur at random and are completely independent of one another. When you get a consecutive string of heads or tails however, these are commonly referred to as “persistent patterns,” which occur no more frequently than other instances of chance (Malkiel, 1999). These unsystematic movements in the short-run are what economists refer to when they state that stock prices follow a random walk.

Unlike the applications of the RWH in the natural sciences, Samuelson (1965) argued that randomness in the stock market is achieved by the active participation of investors who seek to acquire greater wealth. This is a central component of market efficiency and randomness; the assumption that investors seek to obtain greater wealth through their participation in the market. Given their motivated involvement, investors may utilize any and all information that has the potential to provide them with an advantage. In doing so, this information is incorporated into the market prices, which quickly eliminates any profitable opportunities. If such a process occurs instantaneously, then prices must, by way of this incorporation, reflect all available information. This suppresses the possibility for profits to be garnered.

Proponents of the RWH refer to the randomness required to achieve market efficiency as follows: "the more efficient the market, the more random the sequence of price changes generated by such a market, and the most efficient market of all is one in which price changes are completely at random and unpredictable" (Lo & MacKinlay, 1999, p. 4). Note that randomness, in this sense, refers to a "well-functioning and efficient market rather than an irrational one" (Malkiel, 2012, p. 79). It is with this understanding that Fama (1970) encapsulated this concept in his statement that "prices fully reflect all publicly available information" (p. 383).

Studies concerned with utilizing the RWH to explain market efficiency have fallen subject to a host of criticisms. Most notably, Lo and MacKinlay (1999) argue that utilizing the RWH to explain market efficiency is not economically appropriate under all scenarios. Only under certain situations (e.g., risk neutrality), are the two concepts interrelated and equivalent. Moreover, as LeRoy (1973) and Lucas (1978) highlight, the RWH is not a sufficient concept for explaining the efficiency of security prices. Their claims are supported by more recent findings indicating that in the short-term, there is evidence of momentum-based inefficiencies in the stock market (Carhart, 1997; Jegadeesh & Titman, 1993; Lo & MacKinlay, 1999; Rendelman, Jones, & Latane, 1982; Shiller, 2015). These inefficiencies are thought to be a byproduct of the psychological biases of each investor. Notably, De Bondt and Thaler (1985) argue that investors are subject to bouts of optimism and pessimism, depending on the current health of their portfolio. This causes prices to shift from their fundamental values before eventually regressing back to the mean. De Bondt and Thaler (1985) link this reaction to the overreaction that is common of many well-known heuristics. Thus, a contrarian strategy of investing may be the most lucrative as it capitalizes on investor biases.

Despite these objections, a litany of empirical evidence from multiple time series models supports the notion that prices follow a random walk and that price changes occur at random (Cowles & Jones, 1937; Granger & Morgenstern, 1963; Kendall, 1953; Osborne, 1977; Roberts, 1959; Working, 1960). Roll (1992) concludes that true market inefficiency, such as momentum-based inefficiency, should be an exploitable opportunity for an investor. In the absence of these opportunities, it becomes difficult to definitively state that prices are non-random and that they do not incorporate all available information. As Roll (1992) succinctly states, “real money investment strategies [do not] produce the results that academic papers say they should” (p. 28). Malkiel (1999) furthers this sentiment, concluding that movements in the stock market, as well as those concerned with individual stocks, are as random as flips of a fair coin. Taken to a greater extreme, “it means that a blindfolded monkey throwing darts at a newspaper’s financial pages could select a portfolio that would do just as well as one carefully selected by the experts” (Malkiel, 1999, p. 24). Thus, neither historical information nor findings from technical analysis can be used to forecast outcomes or values in the market, which would theoretically render it efficient.

Humans prefer order, not randomness. Despite what the RWH posits, it is commonplace for individuals to search for patterns among truly random events (e.g., stock prices, casino game odds, and sports wagering outcomes). Given the contradictory nature of the empirical results, it is difficult to come to a definitive conclusion that accounts for these two concepts. Nevertheless, it is evident that academic applications of the RWH and the concept of market efficiency have the potential to provide findings that are applicable to both the academic and the practitioner. In particular, the RWH can be used as a tool to determine the randomness of prices. Based on this information, initial conclusions can be drawn regarding market efficiency.

Testable Variations of the Efficient Market Hypothesis

In 1970, Fama proposed a categorized version of the EMH. This included three distinct variations of the hypothesis that depend on the type of information believed to be reflected in the current asset prices (see also Fama, 1991). These three forms are defined as follows: weak, semistrong, and strong. In the weak form of the hypothesis, current prices fully incorporate all information contained in price history and trade volume. In the weak form, historical patterns in the market are believed to have been already exploited to predict future price movement. In the semistrong form, all foundational information about the individual companies, or the market, is accounted for in current prices without delay. Thus, individuals cannot capitalize upon certain pieces of news because all publicly available information will already be included in the company's stock valuation. Note that as traders capitalize on certain pieces of information that they feel will provide them with an advantage, this becomes incorporated into the market prices and thus the potential profitable opportunity disappears. Studies concerned with determining whether publicly available information can be exploited to improve investment performances are generally viewed as tests of the semistrong form (Malkiel, 2012). Lastly, the strong form of the hypothesis asserts that while all that is known is already included in market prices, everything that is knowable has already been incorporated into market prices. Under this form of the hypothesis, even insider trading will not allow traders to achieve long-term profitability. All three versions outlined above form the EMH, yet testing of the appropriate form based on the context under consideration is customary.

Objections to the Efficient Market Hypothesis

Fama (1970, 1991) provides two thorough reviews of empirical work concerned with the EMH. He found that while evidence in support of the theory was extensive, contradictory evidence was virtually nonexistent. Nevertheless, researchers have continued to pursue various angles to reject the EMH. First and foremost, economists attack the fact that the EMH is not a falsifiable theory (de Sousa & Howden, 2015; Fama, 1970). Rather, it relies on assumptions of how the market will operate and fluctuate. In the same manner, it does not provide criteria for measuring efficiency (Alajbeg, Bubas, & Sonje, 2012).

Much attention has also been placed on Fama's (1970) definition of efficiency, or lack thereof. He asserts that "the definitional statement that in an efficient market prices 'fully reflect' available information is so general that it has no empirically testable implications" (p. 384). This concept has led to a host of criticisms levied from economists and researchers who question the fundamental principle of the EMH (Alajbeg et al., 2012; Collier, 2011; de Sousa & Howden, 2015; Lo, Mamaysky, & Wang, 2000). They argue the only way such information could truly be tested is if the market somehow provided a subjective timeline of how this information came into existence, was processed, and eventually came to be reflected in prices (de Sousa & Howden, 2015). Thus, economists and researchers have more concerned themselves with stock price movements than with measuring the flow of information. Modern tests are now not as concerned with market efficiency, but rather statistical analyses that characterize the behavior of markets.

Furthermore, researchers are apprehensive to accept the general premise of the EMH and the concept of a truly efficient market. As first suggested by Grossman & Stiglitz (1980) and noted by Malkiel (2003), "the market cannot be perfectly efficient, or there would be no incentive for professionals to uncover information that gets so quickly reflected in the market prices" (p. 80). Further, the EMH is often refuted by referencing the prolonged financial success of certain investors (e.g., Warren Buffet) and the fact that the stock market has been susceptible to bubbles and crashes. Given these irregularities, it seems rational to assume that the EMH is a flawed concept. For example, episodes such as the 1987 stock market crash, the 2008 housing crisis, and seasonal anomalies such as the "January effect," are all provided as empirical evidence to disprove the theory of market efficiency.

Given these market crises, Shiller (1984) commented that the EMH is "one of the most remarkable errors in the history of economic thought" (p. 459). However, the studies concerned with refuting the EMH are often susceptible to selection bias and fail to become widely accepted because their analyses are too narrow to permit generalization. Schwert (2003) posits that researchers tend to focus on results that challenge preconceived notions or select a combination of variables that will produce statistically significant results in one case, but are not applicable to others. Overall, as Fama (1970, 1991) found in his reviews of published empirical work, there is little evidence to refute the efficient markets model. Patterns of inefficiency are never large or steady enough to ensure perpetually superior returns. This validates the theory of efficient markets (Malkiel, 2003). Moreover, given that the EMH maintains that as information arises it is incorporated into market prices, these historical episodes will never again be useful to investors.

The Influence of Heuristics on Decision Making

Heuristics provide a shortcut with which individuals make judgments given uncertain outcomes. Generally, these processes lead to reasonable and fairly accurate estimates in situations where the outcomes are unknown or the mental processes required to arrive at a decision are complex. The disadvantage of utilizing heuristics, however, is that they subject to systematic and predictable biases. In general, discussions related to heuristic theories are concerned with the biases associated with each concept rather than their sound decision making abilities. These biases generally provide more insight into various components of human decision making which permits researchers to better understand the cognitive processes involved in the processing of information (e.g., Borgida & Nisbett, 1977; Plous, 1993; Tversky & Kahneman, 1973).

The Availability Heuristic

Instances of larger classes are better recalled and more often utilized than those of smaller classes (MacLeod & Campbell, 1992; Tversky & Kahneman, 1973, 1974). More simply, common events are more easily remembered and referenced than uncommon events. The vividness of such information may also influence our decision making, as more vivid imagery or testimonials have been found to outweigh statistical summaries of similar information (Borgida & Nisbett, 1977). By relying on this heuristic, difficult judgements based on frequencies or probabilities can be estimated more simply.

To illustrate this concept, consider the following question posed by Tversky & Kahneman (1973): If you were to randomly select a word from a piece of text in the English language, is it more or less likely that the word will start with the letter *K* or that *K* will be the third letter? Individuals will assess this question by the degree to which both instances come to mind. Generally, it less mentally challenging, meaning that instances are more readily available, to think of words that start with the letter *K* (e.g., kangaroo) rather than those with *K* in the third position (e.g., acknowledge). “If the judgment of frequency is mediated by assessed availability, then words that start with *K* should be judged more frequent” (Tversky & Kahneman, 1973, p. 211). Despite these judgments, a typical sample of text contains twice as many words featuring *K* as the third letter as opposed those that start with *K* (Tversky & Kahneman, 1973).

This example highlights the process by which decisions are made using this heuristic and also illuminates the associated biases. Three common biases associated with the availability heuristic include those due to retrievability, vividness, and imaginability. Biases associated with retrievability will surface when the size of given class is judged by the availability of its occurrences. Salience also affects our ability to accurately assess a given situation based on availability, or lack thereof. For example, when asked if it is more likely to be killed by a shark or a falling airplane part, most people would answer a shark attack. Such a conclusion is supported by the fact that information related to shark attacks is more available and prominent in our memories given then twenty-four-hour news cycle and creation of shark attack movies (e.g., *Jaws*). We arrive at this conclusions despite the fact that the chances of dying from a falling airplane part are nearly “30 times greater than the chances of being killed by a shark” (Plous, 1993). Such a scenario illustrates how the availability and salience of an event may lead to false conclusions.

Concurrently, the vividness of certain events may disproportionally influence an individual’s ability to effectively arrive at a lucid conclusion as to the possibility of an event occuring. For example, vivid descriptions of events, such as terrorist attacks, may exaggerate the possibility that such events could occur in relation to a common crime, such as theft. Since “vivid information is more ‘available’ and easier to recall than pallid information, it often has a disproportionate influence on judgements” (Plous, 1993, p. 126).

Human mental visualization also factors into decision making, especially when an outcome is difficult to imagine (i.e., it has low imaginability). If an individual does not have a memory of an outcome, they will imaginatively generate instances and evaluate the probability of the initial event based on those constructed thoughts. If the instance is easy to imagine, then it will appear more likely to occur and vice versa (Sherman, Cialdini, Schwartzman, & Reynolds, 1985). Moreover, when an event is associated with extremely negative or uncomfortable thoughts, individuals may engage in denial over the chance that such an event will occur (Rothbart, 1970). For example, when asking a fan of a particular sports team what the teams likelihood of success is in the upcoming season, individuals will likely provide answers of optimism, even if the outcome is unlikely.

The availability heuristic is central to the understanding of judgment and decision making. Although definitive conclusions regarding probability estimates are not possible given the elusive nature of everyday events, the subjective probability and availability associated with their occurrences guide human judgment. By understanding the ease at which information comes to mind when one is faced with a making a choice or decision, researchers can better understand the processing strategies and influential factors of human decision making (Schwarz, 1998).

The Representativeness Heuristic

The representativeness heuristic is utilized when making judgments or decisions that are based on whether a situation or event is associated with a certain category and the strength of this association. As such, this heuristic deals primarily with probabilistic questions. In evaluating probabilities, people oftentimes rely on this heuristic to determine the "degree by which *A* is representative of *B*, that is, by the degree to which *A* resembles *B*" (Tversky & Kahneman, 1974, p. 1124). In this process, "one compares the essential features of the event to those of the structure from which it originates" (Tversky & Kahneman, 1973, p. 208). Consider the following example: Max is a very solid and muscular dog who is extremely loyal to his owner and protective of his household. His disposition is fairly serious and he does not often play with other dogs. Would you infer Max to be: a Labrador Retriever, a Cocker Spaniel, or a Doberman? These characteristics would lead us to infer that Max is most likely representative of the stereotype of a Doberman. As such, research has shown that individuals perceive probability and similarity in virtually the same way (Tversky & Kahneman, 1973). The representativeness heuristic is susceptible to arguably the largest amount of biases, as representativeness fails to account for factors that should affect rational probabilistic judgments (Plous, 1993). The most notable biases of this type are detailed below.

In circumstances where descriptions of people or events are not available, some researchers maintain that Bayesian inference is employed (Edwards, 2002; Peterson & Beach, 1967; Tversky & Kahneman, 1971). Bayes' rule is a probability theory that determines the posterior probability of a given event, *A*, after data from *B* has been observed (Bayes & Price, 1763; Edwards, 1968, 1971, 2002). When descriptions are added however, prior probabilities are ignored. This creates a conjunction effect, or a conjunction fallacy, in which individuals perceive that the more information that is provided, the more likely that an event will occur (Tversky & Kahneman, 1983). Rationally, however, the simultaneous co-occurrence of two events cannot be more than the probability of those events occurring separately (Morier & Borgida, 1984; Plous, 1993; Tversky & Kahneman, 1982, 1983). "As the amount of detail in a scenario increases, its probability can only decrease, but its representativeness and hence its apparent likelihood may increase" (Tversky & Kahneman, 1982, p. 98). The representative heuristic is a primary driver of the unwarranted appeal of more detailed information and the illusionary sense of insight that these details provide in arriving at a conclusion.

Contrary to statistical reasoning, individuals tend to fail to account for sample size when utilizing the representativeness heuristic. Termed by Tversky and Kahneman (1971) as the law of small numbers, judgments are made by the proportion included in the sample while omitting reference to the size of the sample. Such a concept is a satirical reference to the law in statistics known as the “law of large numbers,” which posits that the larger the sample you draw from a population, the closer the average of that group will be to the population average. A belief in the law of small numbers suggests that a random sample of a population will resemble the population more closely than statistical sampling would suggest (Plous, 1993). Such a belief violates the foundational concepts of sampling, yet is a common bias associated with this heuristic.

The law of small numbers also explains the misappropriation of chance exhibited by many individuals when engaging in probability judgments. When they have prior knowledge or experience of an event, people often expect that certain characteristics will be represented. For example, when flipping a coin multiple times, we expect that both heads and tails will be contained in the sequence (e.g., heads, tails, tails, heads), as opposed to solely heads or tails (e.g., heads, heads, heads, heads). When subjects are asked to create sequences for tosses of a fair coin, the heads/tails proportions remain much closer to 50% than the laws of chance would suggest (Tune, 1964). The representativeness heuristic leads individuals to disregard the notion of chance in predicting events (Tversky & Kahneman, 1971). This also leads individuals to commit the “gamblers fallacy,” or the belief that a string of “bad luck” events must be followed by a successful outcome (Tversky & Kahneman, 1974). Take lottery drawings for example: after a number has been drawn, the amount bet or the degree to which that same number is selected in subsequent drawings is expected to decline considerably (Clotfelter & Cook, 1993; Suetens, Tyran, & Galbo-Jorgensen, 2016; Terrell, 1994). Similar findings have also been presented for the casino game roulette, in which gamblers expect that a black number is more likely to occur after a string of red numbers (Croson & Sundali, 2005).

Perhaps the most well-known example involving the law of small numbers is the "hot-hand" fallacy. In basketball, a player with a hot-hand is thought to be more likely to convert a basket after one or more successful shots versus having missed the previous shot. Statistical reasoning, however, suggests that the chances of making the next basket are not significantly different from the player's overall chance of making a basket (Camerer, 1989; Gilovich, Vallone, & Tversky, 1985). Detailed analyses of shooting records of the Philadelphia 76er's, Boston Celtics, and the Cornell men's and women's basketball programs by Gilovich et al. (1985) provided no evidence in support of the notion of a hot-hand. Belief in the hot-hand fallacy can be attributed to "a general misconception of chance according to which even short random sequences are thought to be highly representative of their generating process" (Gilovich et al., 1985, p. 295). Nevertheless, players and coaches continue to assess their own abilities and make personnel decisions based on this fallacy, while failing to account for sample size.

Lastly, individuals often fail to take into account trends of general regression. For reference, regression to the mean is a statistical phenomenon in which particularly high or low scores are generally followed by more average scores. Individuals fail to correctly account for this phenomenon for two primary reasons. First, they do not expect regression to occur in the given context, generally due to overconfidence or inhibited reasoning (De Bondt & Thaler, 1985; Shiller, 2015). Secondly, in the presence of regression, they invent false causal explanations (Tversky & Kahneman, 1973). This leads to the overestimation of certain performance measures and underestimates the effectiveness of others. For example, in social interaction and behavior training, individuals tend to believe that punishments are appropriate after poor performance and rewards are suitable following a good performance. This common reward structure fails to account for the concept of regression to the mean, which suggests that after a poor performance, behavior is statistically more likely to improve, regardless of reward. “Consequently, the human condition is that, by chance alone, one is most often rewarded for punishing others and most often punished for rewarding them” (Tversky & Kahneman, 1974, p. 1127). People are generally not aware of this concept and thus fail to account for its influence on the decision making process.

In representativeness, “one compares the essential features of the event to those of the structure from which it originates” (Tversky & Kahneman, 1973, p. 208). In judging the likelihood of an event based on the observations of similar events, one forms decisions based on representativeness reasoning. While this heuristic is useful in probabilistic decision making, one must be aware of the associated biases when analyzing this process. Failure to account for these biases leads to systematic errors in judgment.

Criticisms of Heuristic Theories

The concept of heuristics and their associated biases have promulgated a host of criticisms (e.g., Barone, Maddux, & Snyder, 1997; Gigerenzer, 1991; Macchi, 1995;

Ortmann & Hertwig, 2000; Schwarz, Strack, Hilton, & Naderer, 1991). Constraints on the present paper do not provide space for a detailed review, but central criticisms focus on the general pessimistic account that heuristic theory offers of human behavior, the representativeness and generalizability of empirical findings, and a failure to account for ecological validity. A common critique regarding heuristic research is that it offers a negative outlook on one's "ability to make sound and effective judgments" (Gilovich & Griffin, 2002, p. 8). Critics note that humans have "split the atom, recombined DNA, and travelled to the moon" (Gilovich & Griffin, 2002, p. 8), feats that they may not have been able to accomplish if their judgments were constantly biased. Thus, some critics view heuristic research as unproductive because it belittles "human decision makers as systematically flawed bumblers" (Ortmann & Hertwig, 2000, para. 2).

Another critique stems from the notion that research in support of heuristic decision making may be nothing more than a laboratory hoax. There are a set of assumptions that undoubtedly accompany participation in a psychology experiment. These may influence how human subjects behave; participants may misconstrue a question or fail to anticipate how a certain stimulus will influence judgment, which may skew results or limit the generalizability of findings. Data may also be influenced by the effects of "experimenter bias," which describes the phenomenon in which an experimenter's behavior may influence the participant's responses in an unintended way (Doyen, Klein, Pichon, & Cleeremans, 2012; Rosenthal & Rubin, 1978). If a researcher is more motivated to validate his or her a priori conclusions rather than understand the true nature of the human decision making process, they may subconsciously pose misleading questions to study participants. These criticisms illustrate the point that one should be mindful of the context and lab setting in question when analyzing and ultimately generalizing the findings of heuristics-based research.

Closely related to the issues stemming from laboratory studies is the belief that such research fails to account for ecological validity. As described by Brunswik (1937, 1956, 1957), ecological validity is the degree of correlation between a proximal cue and a distal object variable.[1] Within our natural environment, these cues influence our perception and ultimately our decision making. For example, in a test of perception, one may assess the correlation between vertical position (proximal cue) and size of an object (distal object) since larger objects tend to be higher in our field of vision (Hammond, 1998). Heuristic research places an emphasis on the identification of the cues that humans use to make judgments, but fails to assess the true value, or ecological validity, of the cues themselves (e.g., Schwarz, et al., 1991; Schwarz & Vaughn, 2002). To do so would require the identification of all relevant objects in a specific subject area and subsequently classifying each object given the value of the cue variable (Gilovich & Griffin, 2002). Such a task would require a large number of resources thus heuristic research has placed focus on the identification of cues rather than evaluating the significance of those cues.

While the various criticisms of heuristics-based research are important to note, it is evident that findings in support of heuristic theory span a robust and varied set of contexts that detail human interaction. These findings contribute to useful theoretical

[1] This concept should not be confused with the term representative design, which deals with how well the setting within which the experiment was conducted represents similar environmental conditions (Brunswik, 1956).

constructs that help to explain the principles and constraints on the human decision making process.

Sport Wagering Market Constructs

Before reviewing the literature concerned with measuring market efficiency in sport wagering markets, it is imperative to understand the basic constructs and the role of bookmakers in these various markets. Most importantly, there are a host of parallels between trading in the financial sector and sports wagering that permit the use of the aforementioned financial theories. In both arenas, investors, or bettors, with varied beliefs and sources of information, seek to profit through trading propositions that resolve over time. Unlike the stock market where prices are infinitely lived, outcomes in the various sport wagering markets are instantaneously known at the conclusion of a given contest, making them prime subjects for empirical analysis. Furthermore, in both settings, participants engage in a zero-sum proposition, meaning that there is a winner and a loser in each transaction. This allows for further evaluation of the financial impact that the outcome has on either party.

Lastly, the magnitude of these markets makes them attractive for both investors and researchers. As previously mentioned, the sport wagering industry is estimated to be worth roughly $1 trillion. This rivals many of the world's largest financial markets, such as the New York Stock Exchange, the world's largest Initial Public Offering provider, which is estimated to hold over $1 trillion in market capital (Desjardins, 2016). The size of the sport wagering industry makes it a compelling avenue for exploration, as findings have the potential to appeal to a large portion of the population.

Despite these similarities, it is important to note the way in which these markets differ. Prices in the financial sector fluctuate and change frequently, where the final price is set at a level that matches supply with demand. Thus, market makers set prices to match buyers with sellers. In contrast, oddsmakers, or bookmakers, generally set an initial price that is subsequently adjusted in small increments to varying frequencies. Two primary schools of thought have emerged regarding the role of bookmakers. On one hand, researchers and industry experts believe that oddsmakers set prices that equalize the number of wagers on each side of a given proposition. That is, they attempt to match supply with demand to limit their risk and ensure a profit, regardless of the outcome. If the initial price is incorrect or inefficient, however, the bookmaker may subject himself to a large degree of risk, especially if informed bettors capitalize on the pricing error. Nevertheless, bookmakers are believed to incorporate all publicly available information while also accounting for common bettor biases when setting the final closing line.

Conversely, the other school of thought maintains that bookmakers do not set prices to equalize the amount wagered on both sides. Rather, bookmakers set prices that exploit bettor biases. This allows them to capitalize on their ability to predict outcomes more accurately than the average bettor. Thus, oddsmakers themselves become active participants in the wagering process. As a result, greater profits can be obtained than if prices were set in the traditional market sense in avoidance of substantial risk. Give that there are some bettors who are as skillful in picking games as the bookmakers, dollar limits on how much money can be wagered are set by sportsbooks to limit the distortion of prices from reaching a point that could create profitable opportunities (Levitt, 2004). Thus, one could make the case that the true difference between the financial and sport wagering market lies in the ability of a small set of individuals to predict game outcomes more accurately than the general public. In the financial sector, "the flow of inside information or the inherent complexity in valuing companies may make it impossible for one individual to do better than the market, meaning that a market maker who acted like a bookmaker would do worse than one who simply equilibrated supply and demand" (Levitt, 2004, p. 245). Such a claim is supported by the lack of evidence regarding the ability of investors to beat the market over a sustainable period.

Most empirical research assumes that bookmakers do not take informed positions against bettors. As L. M. Woodland and B. M. Woodland (1994) point out, when bookmakers do not attempt to balance the wagers, their earnings become dependent on the outcome of a given contest. Thus, "questions of market efficiency cannot be addressed because subjective probabilities are revealed only when the books are balanced" (L. M. Woodland & B. M. Woodland, 1994, p. 272). While this study will operate under the balanced book assumption, it is important to note that two different schools of thought exist within the various sport wagering markets.

There are three primary outcomes on which bettors can wager in the NFL, NBA, MLB and NHL: the point spread, which is a bet on a point differential between opponents, the moneyline or oddsline, which is concerned with solely selecting the winner in a contest, and the total line, which requires the bettor to select whether the combined score of both teams will go over or under the line set by the bookmakers. Hereafter, each of these outcomes will be referred to as markets (e.g., the totals market). For further clarification, sample betting lines for an NFL game are provided below.

Table 2.1

Sample NFL Betting Lines

Team	Point Spread	Money/OddsLine	Total
Denver Broncos	–7.5	–110	Over 47
New England Patriots	+7.5	+110	Under 47

In this example, the Denver Broncos are considered the visiting favorite while the New England Patriots are the home underdog. If the bettor were to wager on the point spread, he would need to choose either that the Broncos would win by more than 7.5 points or that the Patriots would lose by less than 7.5 points. A wager on the moneyline would require the bettor to wager $110 to win $100 if he favored the Broncos, or $100 to win $110 if he believed that the Patriots would win. Lastly, a wager on the total, which is not connected to either team, would require the bettor to decide whether the two teams would score over a combined 47 points or under a combined 47 points. If the final score features a total that is exactly 47, then the bet is considered a push and all money is returned.

In addition to a basic understanding of these markets, it is also necessary to understand the concept of a fair bet and profitability. Violation of a fair bet, or an efficient market, occurs when a win percentage for a certain betting strategy deviates from 50%, setting the null hypothesis for a fair bet at 50%. For example, if consistently betting on the home team to beat the spread in the NFL yields a win percentage of 57% and this was found to be significantly different from chance (50%), this strategy would violate the null of a fair bet.

The \$11/\$10 (–110, 100) betting rule implies that bettors wager \$11 to win \$10, known as flat odds. Within sports betting, a flat bet is always booked at odds of 11 to 10 regardless of the market or sport. Under the \$11/\$10 betting rule, profitability is realized when a win percentage of 52.38% is achieved and found to be statistically significant, as initially suggested by Vergin & Scriabin (1978). The following equation details the determination of the proportion of a winning bet by setting expected winnings equal to expected losses.

$$P(\$100) = (1 - P)(\$110)$$

or

$$P * \$100 + (1 - P)(-\$110) = 0$$

P refers to the probability of winning a wager (i.e., the "break-even probability"), and signifies the probability of losing the wager. \$100 and –\$110 correspond to the initial odds on which individuals wager. From these equations, the break-even probability, *P*, is .5238, indicating that the chances of a bettor neither earning a profit nor losing money is .5238, or 52.38%. This figure also accounts for the commissions, or vigorish, paid to bookmakers by factoring in the initial odds (Vergin & Scriabin, 1978).

While bets in the NFL and NBA on the point spread and totals occur at \$11/\$10 odds, in the MLB and NHL these lines are posted with an odds adjustment. This is due to the smaller variance of scoring in the MLB and NHL, which forces bettors to wager additional money on the more popular side of the proposition in order for bookmakers to better balance the number of wagers on each side (Paul & Weinbach, 2004). Thus, while the 52.38% is the standard, the measure of profitability must be recalculated if the odds are variable.

Wagering markets are essentially simplified financial markets. Both operate under the premise that prices are inclusive of all publicly available information, while investors, or bettors, seek to profit by trading on outcomes that are uncertain. Through analysis of publicly available information, individuals largely believe that they can beat the market in a manner that will allow them to enjoy above-average returns. Moreover, sports betting, much like financial trading, is “a zero-sum game with one trader on each side of the transaction” (Levitt, 2004, p. 223). Sport gambling markets do provide a unique aspect, however, which make them prime for measurement under the EMH: they have a definitive start and end. This makes the processing of profits and losses much quicker (Paul, Weinbach, & Wilson, 2004). To this point, Thaler and Ziemba (1988) note, “Since a stock is infinitely lived, its value today depends both on the present value of future cash flows and on the price someone will pay for the security tomorrow” (p. 162). In contrast, the payout of a wager is immediately determined once the contest has ended. Thus, “wagering markets can provide a clear view of pricing issues which are more complicated elsewhere” (Sauer, 1998, p. 2021).

The Efficient Market Hypothesis and Sport Wagering Markets

Pankoff (1968) spurned the testing of market efficiency in sports wagering markets and specifically directed the focus on point spreads. His initial study, which utilized a regression-based model, found that market inefficiencies in the NFL were too minute to detect. This motivated a line of empirical research focused solely on point spreads via a host of regression-based analyses (Gandar, Zuber, O’Brien, & Russo, 1988; Golec & Tamarkin, 1991; Sauer, Brajer, Ferris, & Marr, 1988; Vergin & Scriabin, 1978). Notably, Vergin and Scriabin (1978) found reasonable evidence to suggest that the NFL’s point spread market was inefficient. However, Tryfos and colleagues questioned these findings, citing statistical errors that may have resulted in the inaccurate reporting of profitable statistics (Tryfos, Casey, Cook, Leger, & Pylypiak, 1984).

More recent studies have found clear violations of an efficient market under the favorite-longshot bias. Well-documented in horse racing, this bias implies that longshots, or underdogs, are over bet in relation to favorites in the hopes of larger payouts. In the mainstream sports arena, the reverse of the favorite-longshot bias, where favorites garner more wagers than the underdog, has resulted in consistent returns to the underdog bettor (Gandar et al., 2004; Gandar et al., 2002; B. M. Woodland & L. M. Woodland, 2010; L. M. Woodland & B. M. Woodland, 1994, 2001, 2003). Such a bias is said to stem from bettors who incorrectly price the contests and fail to properly assess the likelihood of certain outcomes. These biases may be attributable to certain heuristics that lead to misperceptions regarding the probabilities of certain outcomes. Studies relating to this topic have largely utilized heuristic applications to account for bettors' gambling beliefs, including the gamblers fallacy and an aversion to accept losses without explanation (Gilovich, 1983; Wagenaar, 1988). As of yet, few empirical studies have been conducted that evaluate the degree to which heuristics explain sports gambling behavior in particular.

While market factors undoubtedly play a role in these findings, adjustments and advancements in statistical analyses should not be ignored. Instead of the basic regression model used by Pankoff (1968) and many of the early studies, recent research now uses more advanced ordinary least squares and probit regression models. These recent studies generally include additional predictors and more complete data that allow for more accurate conclusions to be drawn.

Researchers now have the opportunity to explore less-publicized betting constructs, such as the totals market, due to advancements in betting technologies and data availability. The totals market, in particular, creates an interesting avenue for research, given that bettors have a known affinity towards over bets. As Paul and Weinbach (2002) note, "psychologically, if a gambler has a rooting interest in his or her bet and is not just viewing the activity as an investment option, it makes logical sense that the over becomes a more popular bet than the under, as rooting for scoring tends to be easier than cheering for a lack of scoring" (p. 259). The remainder of this review will be primarily concerned with the literature focused on the totals market in the four major North American professional sporting leagues.

National Football League

Initial analyses of the totals market in the NFL conducted by Even and Noble (1992) and Gandar, Zuber, and Russo (1993) found evidence of no inefficiencies or profitable betting strategies within the NFL's totals market. Conversely, Kochman, and Badarinathi (1996) found that while widespread opportunities for profitability were not present, team-specific opportunities did emerge. Paul and Weinbach (2002) carried out possibly the most extensive study in this market, analyzing totals from the seasons spanning 1979–2000. While their findings did reveal that the overall market was efficient, there were instances where profitability could be achieved for particularly high point totals. Starting with the totals that were set 5, 6, and 7 points away from the sample mean of 40.3, their results indicated a rejection of the null of a fair bet in all three subsets of games for the under bettor. For the games farthest from the sample mean, the null for a fair bet and profitability were rejected. This finding runs counter to the psychological underpinnings of most gamblers who view gambling on sports as a recreational activity. Those who view the game with a rooting interest are more likely to cheer for scoring as opposed to a lack of scoring (Paul & Weinbach, 2002). The findings of Paul and Weinbach (2002) have motivated studies of high point totals and inefficiencies in other professional leagues. The authors do note, however, that such a strategy in the NFL is not likely to last, given the efficient nature of gambling markets.

National Basketball Association

The market for totals in the NBA has received little research attention. As in the NFL, Paul, Weinbach, and Wilson (2004) found empirical evidence to suggest a violation of a fair bet for the highest point totals. Starting with the total line of 200, the totals measured were increased by one point until they reached 210, which was the last total with sufficient observations to accurately conduct statistical analyses. For totals greater than 202, 204, 206, 207, and 208, the null of a fair bet was rejected for the under bettor (Paul et al., 2004). For the same totals however, no evidence was found to reject the null of no profitability. Much like in the NFL, the psychological preference of bettors to wager on the over should be noted.

Given that the totals market in both the NFL and NBA operate with an identical flat-odds structure, this highlights the question of why informed bettors do not adopt a contrarian approach to the public and drive the total line back to its efficient value. The economic answer may be found in the limits placed on the different markets. In the NFL totals market, limits on single bets can vary between $2,000 and $5,000, while in the

NBA limits average around $2,000 (Paul et al., 2004). As the betting action pours into the various sports books, lines are adjusted to even the betting on both sides of the proposition. Generally, members of the public will shift lines away from their true market value, which creates profitable avenues for certain informed bettors. For example, expert bettors, or “wise guys,” in the point spread market, where limits are much higher, can wager enough money on a given side to drive the line back to an efficient value. This thwarts the possibility for the average bettor to achieve consistently high returns. However, the low limits placed on the totals markets “restrict the possibility for informed wise guys to bet a large enough amount to drive the line back to its efficient value” (Paul & Weinbach, 2002, p. 261). Since per-game betting volume is lower in the NBA than in the NFL, it is more likely that informed bettors in the NFL market have the potential to eliminate profitable opportunities that may arise when the line deviates from its efficient market value.

Major League Baseball

Counter to the flat-odds market structure present in the NFL and NBA, the MLB and NHL employ a variable odds model. For example, the total line the MLB may read as follows:

Colorado Rockies at Los Angeles Dodgers: 11over-130; 11under+110

This is commonly referred to as a 20-cent line because the difference between 130 and 110 (ignoring positive/negative signs) is 20. In this scenario, the closing total is 11 runs with an over bettor wagering $130 to win $100. Conversely, the under bettor would have to bet $100 to win $110. Given this, Brown and Abraham (2002) found that over/under outcomes tended to miss in streaks. More specifically, betting that a team’s win streak against the posted total would continue was found to be profitable for the 1997 season. Such a finding was not found to exist in any other season studied. Brown and Abraham (2002) suggested that this unique result could be attributable to the expansion, realignment, and introduction of interleague play during the 1997 season, as similar inefficiencies disappeared for the 1998 season.

This initial study sparked a debate among researchers concerned with Brown and Abraham’s (2002) failure to include odds in their initial analysis. Instead, they opted to follow a simple strategy of determining win percentages over 54.5% as profitable. Paul and Weinbach (2004) commented that the findings should not be considered valid, as the study failed to properly calculate profits and losses. The implied odds of Brown and Abraham (2004) took the form of a 40-cent line (uncommon in the baseball totals market). Furthermore, the authors failed to provide corresponding odds adjustments for each game, instead utilizing a simple break-even point of 54.5%.

Brown and Abraham (2004) replied to Paul and Weinbach’s (2004) comment by stating their estimates of efficiency were conservative and that use of a 20-cent line would have deemed even more of their strategies as profitable. Further, the authors stated that their original research was concerned with betting on streaks, not necessarily with the exact amount of dollars won. Also providing commentary on this debate, Gandar and Zuber (2004) supported the claims of Paul and Weinbach (2004). They maintained a constant break-even proportion is not appropriate for testing profitability in this market. They went on to conduct their own analysis, which asserted that there is no way to confirm the returns for the original strategy proposed by Brown and Abraham (2002) without the inclusion of the actual odds. Thus, the findings of Brown and Abraham (2002) should be interpreted and applied with caution.

Bickel and Kim (2014) is the most recent study concerned with this market. This study accounted for the issues highlighted by the previous debate by including individual game odds in the analysis. Little evidence was found to suggest the market was inefficient. The authors did find some season-specific inefficiencies, but these were isolated and did not translate from year to year.

National Hockey League

While markets in the NFL, NBA, and MLB have received the most research attention, the NHL market remains largely understudied. While a host of factors may be attributable to the lack of previous literature, one contributing factor is the fact that the NHL was the last of the four major North American sports to be integrated on a consistent level by sportsbooks (L. M. Woodland & B. M. Woodland, 2001). That is, all NHL games and betting lines were not always offered for wagering purposes. Like the totals market for the NFL and NBA, B. M. Woodland and L. M. Woodland (2010) found that a clear under bias existed in the NHL totals market, especially for high goal totals. The EMH was rejected in multiple cases with limited opportunities for profitability. The degree of inefficiency and profitability found in this market suggests that it is the least attuned in terms of appropriately pricing contests of the four major sports. B. M. Woodland and L. M. Woodland (2010) failed, however, to account for the odds associated with each total. They utilized a simple strategy of denoting profitability when win percentages exceed 52.38%, which has been proven to be insufficient in the variable odds markets (Gandar & Zuber, 2004; Paul & Weinbach, 2004).

Heuristic Theories and Sport Wagering Markets

The application of heuristics to specific sports betting markets and the extent to which these concepts can explain market efficiency and bettor behavior has been undertaken by a few recent studies (B. M. Woodland & L. M. Woodland, 2015, 2016; L. M. Woodland & B. M. Woodland, 2015). Recall that market efficiency and the EMH suggest that it is impossible for investors to consistently earn above-average profits because markets fully reflect all publicly available information with little or no lag time (Fama, 1965; Samuelson, 1965). These studies examined the efficiency of the season wins total markets for the NFL, NBA, and MLB. In the season wins total market, oddsmakers set a line that represents the total number of games they believe a certain team will win over an entire season, excluding the playoffs. Note that since the posted odds are only applicable to a single team and not a contest, there is no identifiable favorite or underdog. Research concerning the NHL season win totals market has yet to be conducted, possibly due to the lack of available data.

L. M. Woodland and Woodland (2015) proposed several betting strategies for testing the efficiency of the NFL wins total market. They found the market to be highly inefficient, citing several strategies for profitability. L. M. Woodland and Woodland (2015) posited that inefficiencies may be driven by the representative heuristic, in that bettors tend to overreact to recent information and fail to account for certain biases, including regression to the mean. Another potential explanation for these profitable returns may lie in the makeup of the market. Betting volumes in this market are significantly lower than those in other markets. At the Mirage in Las Vegas, for example, bettors can wager up to $100,000 on a point spread bet in the NFL. Conversely, the limit on the season wins totals market is closer to $2,000 at the same casino (L. M. Woodland & B. M. Woodland, 2015). These low limits, coupled with the fact that this type of wager takes at least four months to pay out, may explain the desire for expert bettors to spend their money elsewhere.

In the NBA, B. M. Woodland and L. M. Woodland (2015) found the market to be more efficient than in the NFL, yet profitable returns still emerged for certain strategies. An explanation for this finding is that the NBA may attract a more sophisticated bettor than the NFL. As Reber (1996) posited, “basketball has historically attracted the most sophisticated sports bettors, folks who are more knowledgeable about the game than those who bet [on] football and baseball” (p. 309). Sophisticated bettors such as these may be able to avoid the pitfalls of heuristic-based inefficiencies, such as betting against public opinion or failing to account for regression to the mean. However, the authors note that there were instances in which bettors overvalued a team’s performance in past seasons. These bettors associated past performance with future outcomes, a trait indicative of the representativeness heuristic.

The authors further posit that the presence of “glamor” teams may provide a potential explanation for profitability measures. As Egon, Verbeek, and Nuesch (2011) concluded, “more glamorous teams have a larger fan base and are, therefore, more prone to attracting sentiment bets. In essence there is ceteris paribus an excessive proportion of stakes placed on the relatively more popular team winning” (p. 505). In the NBA, the Los Angeles Lakers qualify as a glamor team and are largely overbet by recreational bettors whose betting interests lie in entertainment. Furthermore, Flepp, Nuesch, and Franck (2016), suggest that bettors are susceptible to a loyalty bias, which prohibits them from betting against their favorite team. Consideration of the influential power of sentiment and loyalty biases motivated B. M. Woodland and L. M. Woodland (2015) to rerun their analyses for only the Los Angeles Lakers. They found that bettors drastically overbet the glamor team, creating a clear inefficiency for the under bettor. These findings confirm the sentiment bias proposed by Egon et al. (2011) as well as the loyalty bias identified by Flepp et al. (2016).

Like the NFL and NBA, the MLB season wins total market was found to be inefficient with opportunities for profitability given certain betting strategies. B. M. Woodland and L. M. Woodland (2016) found that bettors exhibited a clear tendency to overvalue a team’s performance in a previous season, especially if they achieved a winning record. Much like the NFL season wins total market, bettors failed to account for the regression to the mean concept. These mispriced strategies yielded results that were stronger than those for the NBA, yet weaker than those in the NFL. Successful strategies were generally limited to the under bettor, which is consistent with previous research indicating that the bettors prefer the over wager when it comes to the totals market (Paul & Weinbach, 2002). In the season wins total market, instead of cheering for points, bettors root for wins, which may contribute to these inefficiencies.

Sports wagering markets provide an optimal framework to test the theory of an efficient market. The literature concerning market efficiency in the professional sporting leagues has been extensive, yet lopsided. Much of the research has focused on the point spread market in the NFL, which has left a gap in the literature concerning other markets, specifically the various totals markets. Although minimally studied, these markets appear to feature a level of inefficiency with trace opportunities to achieve profitability, especially for high point/goal totals. Though largely overlooked, the totals market provides an optimal setting within which to measure market efficiency where complete data has become readily available. Furthermore, the NHL, in comparison to the NFL, NBA, and MLB, has experienced the most significant changes to its league structure through the formation of new teams, realignment of conferences, and the creation of four separate intra-conference divisions (Pacific, Central, Metropolitan, and Atlantic). These changes may contribute to more recent inefficiencies not captured by previous studies. Thus, a clear opportunity exists to further examine this market to uncover potential inefficiencies.

CHAPTER III

METHODOLOGY

This study focused primarily on semistrong tests of market efficiency. That is, tests were conducted based on both historical and readily available public information. As described in Chapter II, Fama (1970) proposed three variations of the EMH: weak, semistrong, and strong. The semistrong form of the EMH is inclusive of the weak form, in that current prices are independent of past prices. For the purposes of the present study, it was assumed that bookmakers set prices to balance wagers (as opposed to taking a vested position against bettors). Given this assumption, it was possible to draw conclusions regarding market efficiency and expected returns. As L. M. Woodland and Woodland (1994) noted, unbalanced books cannot be used to study market efficiency "because subjective probabilities are revealed only when the books are balanced" (p. 272, note 7).

A previous study concerned with measuring market efficiency in the NHL totals market found evidence of an under-bias, especially for high goal totals. That is, bettors preferred to wager on the over, which created profitable opportunities for the under bettor (B. M. Woodland & L. M. Woodland, 2010). Similar under-biases were also reported for the NFL and NBA (Paul & Weinbach, 2002; Paul et al., 2004). More specifically, Paul & Weinbach (2002) noted, "psychologically … it makes logical sense that the over becomes a more popular bet than the under, as rooting for scoring tends to be easier than cheering for a lack of scoring" (p. 259). These findings informed the present study on a foundational level. Five strategies were then devised based on publicly available information and common behavioral biases (e.g., heuristics). Statistically, this analysis was concerned with significance tests of win proportions from the vantage of the under bettor. Once these initial win proportions were computed and assessed, more in-depth tests that focused on expected returns were completed.

The remainder of this chapter is divided into the following sections: (1) betting strategies, (2) data, (3) variables, (4) hypotheses and statistical analyses. The first section lists the betting strategies that were tested in this study. When appropriate, the heuristic that informed the particular strategy will be identified. Next, a description of the data is provided to frame the scope of the study. The variables section provides a description of all variables to be considered and calculated. Lastly, the final section outlines the hypotheses that were tested, and statistical analyses utilized, to conduct the tests of market efficiency and profitability.

Betting Strategies

The following strategies formed the basis of this research and were largely motivated by the availability and representativeness heuristics. When appropriate, the heuristic associated with a specific strategy will be identified and explained.

- Strategy 1 – Cumulative Outcomes: Bet the under for all games, regardless of odds. Such a strategy is commonly investigated by studies concerned with totals betting (e.g., Paul & Weinbach, 2002; Paul et al., 2004). Moreover, this strategy tested whether bettors in this market exhibited a similar behavior to those in the NFL (Paul & Weinbach, 2002) and NBA (Paul et al., 2004), and NHL (B. M. Woodland & L.

M. Woodland, 2010) in that a preference for scoring creates profitable opportunities for the under bettor.

  - Strategy 1a: Further examination of Strategy 1 for each closing total. Reminder, the closing total is the final betting line (e.g., over/under and odds pairing) offered before the start of a game.
  - Strategy 1b: Bet the under whenever the over closing total odds were favored in relation to the under odds. This approach simply segmented the population further in an attempt to uncover inefficiencies related to previously documented under-biases.

- Strategy 2 – The Hot-Hand Fallacy: Bet the under in games that featured two teams with an at or above .500 average against the over total in their previous five games. This strategy was concerned with the representativeness heuristic and the likelihood of bettors to associate past outcomes with future events. Therefore, inefficiencies may be attributable to the hot-hand fallacy and failure to account for general regression concepts.
- Strategy 3 – The Glamor Effect: Bet the under in games that featured one or two glamor teams. That is, teams that ranked in the top 15 in terms of popularity (variables related to popularity are detailed below). This strategy was grounded in the representative heuristic and, more specifically, sentiment bias, wherein bettors tend to overvalue more popular teams.
- Strategy 4 – Playoff Success and Recency Bias: Bet the under in all games that featured one or two playoff teams from the previous year. This strategy was concerned with the availability heuristic and the tendency for bettors to exude a

recency bias. This may lead to inflated totals as bettors may overvalue the scoring potential of these playoff teams thus skewing closing totals.

- Strategy 5 – The Conjunction Fallacy: Bet the under in all games that featured one or two teams ranked in the top 15 in terms of analytic variable average in the previous season. Inefficiencies may be explained by the conjunction fallacy and the perception that the more information that is provided, the more likely a specific event will occur.

Data

The data utilized for this study was drawn from multiple sources. All game and betting-specific information was obtained from oddswarehouse.com, a website dedicated to providing historical sports betting odds. Playoff teams were identified based on information readily available from NHL.com. Analytic rankings were gathered from hockey-reference.com. Glamor team rankings were assigned based on a fan engagement analysis conducted by Lentile (2013).

The seasons studied for this analysis spanned from 2011/12 to 2016/17. This timeframe was selected as it featured consistency regarding the number and location of teams. More specifically, in 2011 the Atlanta Thrashers relocated and became the Winnipeg Jets. After this move, no relocation or expansion teams emerged during the sample period. Thus, to avoid any statistical errors or biases concerned with team relocation, the 2011/12 season was deemed an appropriate starting place.

In total, 6,105 regular season games made up the sample less all push bets and playoff games. Push bets (n = 761) were excluded because there was no true winner from a gambling perspective. Recall, these outcomes occur when the combined number of goals scored equals the closing total. Playoff games (*n* = 528) were excluded for two reasons. First, their inclusion held the potential to create additional biases and/or inefficiencies not accounted for in this study. Second, these potential biases could not be deduced without additional statistical procedures that were beyond the scope of the present study.

Variables

To appropriately gauge the efficiency and profitability of this market, a host of variables and calculated statistics were assessed. Table 3.1 provides a listing of all variables drawn from the data sources, along with their corresponding notation and a brief description. Note that the combination of Under Close Odds (UCL) and Over Close Odds (OCL) are what form odds pairings.

Table 3.1

Data Source Variables

Variable	Notation	Description
Home/Away Team	HT/AT	Coded 1-30 in alphabetical order by city.
Home Score	HS	Total number of goals scored by the home team.
Away Score	AS	Total number of goals scored by the away team.
Closing Total Line	CL	Closing total line set by bookmakers.
Under Close Odds	UCL	Odds associated with the closing under total line.
Over Close Odds	OCL	Odds associated with the closing over total line
Total Score	TS	Combined number of goals for both teams.
Betting Outcome	BO	Result based on the closing total. Coded as 1 for a winning under bet, 0 for a winning over bet.
Over Win Percentage	OWP	Number of wins and losses against the total line for each team reported as a running percentage.
Playoff Team	PT	Indicates that a team made the Stanley Cup Playoffs the prior year. Coded as 1 if true and 0 otherwise.
Glamor Team Ranking	GT	Coded as 1-30 and remained constant from season to season.
Analytic Rank	AR	Coded 1-30 and changes each season. 17 total variables were factored into the ranking.

Three variables require additional explanation. First, glamor teams were identified using the results of a study conducted by Lentile (2013), who considered five criteria when ranking the popularity of each NHL franchise: Google search results, franchise Facebook likes, team Twitter followers, franchise worth, and spectator attendance. The results and subsequent rankings were utilized for each season in this study. Unfortunately, no updates to this study were made nor were there comparable studies done prior to or after 2013, which eliminated the possibility to update the rankings each seaon. However, it is reasonable to assume that glamor teams, given the seasons analyzed, remained relevant and constant.

Second, analytic ranks were assigned using aggregated average scores of 17 variables related to performance. The variables and their descriptions can be found in

Table 3.2. Third, over win percentage (OWP) was calculated as a team-specific running percentage that reset after each season. More specifically, this figure was indicative of the number of times that the final score went over the closing total line in the teams' previous five games. While it is understood that final scores are representative of efforts from both teams, it is not uncommon for fans to attribute the scoring success of two teams to a single team in a forthcoming matchup. The remaining variables were simplistic in their makeup and are commonly referenced throughout hockey and betting communities.

Table 3.2

Analytic Variables

Variable	Description
Corsi For (CF)	Shot attempt differential for a particular team.
Corsi Against (CA)	Shot attempt differential for all opposing teams.
Corsi For % (CF%)	CF% above 50% indicates that a team controls the puck more often than not.
Fenwick For (FF)	Shot attempt differential for a particular team, with blocked shots removed.
Fenwick Against (FA)	Shot attempt differential for all opposing teams, with blocked shots removed.
Fenwick For % (FF%)	FF% above 50% indicates that a team controls the puck more often than not.
Team on-ice shooting percentage (oiSH%)	Team shooting percentage.
Team on-ice save percentage (oiSV%)	Team save percentage.
Team on-ice shooting percentage (oiSH%)	Team shooting percentage.
Team on-ice save percentage (oiSV%)	Team save percentage.
offensive Zone Start % (oZS%)	Number of a times a team starts in their offensive zone.
defensive Zone Start %(dZS%)	Number of a times a team starts in their defensive zone.
PDO	The efficiency of a team's shots and their ability to stop the opponents' shot.
Faceoff Wins (FOW)	Number of faceoff wins.
Faceoff Losses (FOL)	Number of faceoff losses.
Hits (HIT)	Total number of hits.
Blocks (BLK)	Total number of blocks.

Hypotheses and Statistical Analyses

Although findings of economic inefficiency are not uncommon in sport wagering markets, rarely are there consistently profitable opportunities for bettors. Recall that in a truly efficient market, no formulated strategy should yield higher returns than one simply comprised of randomly selected wagers nor should there be opportunities for sustained above-average returns. Given that totals in the NHL are set with an odds adjustment, tests of win proportions based on a 52.38% break-even win percentage, which is only appropriate for flat odds (-110, +100), should not be considered valid. Rather, more comprehensive tests must be conducted that consider each odds pairing. L.M. Woodland and Woodland (1994, 2001), have been credited with the first odds-specific study of market efficiency. Gandar et al. (2002, 2004), amended those tests to provide more stringent examinations of market efficiency. For the purposes of this study, the derivations and specifications presented by Gandar et al. (2002, 2004) were utilized.

Before attempting to calculate any market statistics, it is imperative that the notation for favorites and underdogs is understood. Favorite and underdog prices were identified as β_1 and β_2, respectively, throughout this analysis. Note that in this market, there is no favorite or underdog in the traditional sense. These notations were solely used to label prices, not teams. For example, given the odds (-110, +100), β_1 would be written as 1.1 while β_2 would be notated as 1.0. These decimal values, or decimal odds, were calculated by taking the absolute value of the initial odds figure and dividing by 100 (e.g., |-110|/100). In some instances, however, lines in the NHL are offered where both the underdog and favorite bettors must wager more than their expected winnings. This generally happens when teams are evenly matched, or no clear distinction has been made by oddsmakers on the teams' goal scoring potential. These lines are referred to as double-negative lines (e.g., -115, -105). In the scenario provided, -105 (1.05) would be considered β_2, as bettors would need to wager a smaller amount to win a $100 compared to the -115 (1.15), β_1, odds. Now that the notation for favorites and underdogs is understood, tests of market efficiency can be properly conducted.

To appropriately assess this market and each strategy, a two-step process was utilized. First, tests of market efficiency were conducted for each betting strategy. Given that each strategy is unique in its structure, sample size varied depending on the number of contests that met the requirements of each strategy. However, a minimum number of contests for each odds pairing was established in order to ensure normal distribution of the data. These limits are notated within the results tables for each strategy. Regardless, the statistical analyses employed were identical.

The null hypothesis of efficiency implies that the objective probability of an under wager win equals the subjective probability of an under wager win. Otherwise, the expected losses would not be equivalent for both sides. Thus, the hypothesis for market efficiency is characterized by the following

$$\text{HO1: } \pi = \rho$$

$$\text{H1: } \pi > \rho \text{ or } \pi < \rho$$

where π is the objective win probability and ρ is the subjective win probability for a given odds pairing from the vantage of the under bettor. Given the symmetry of betting data, it is appropriate to study each game from only one betting perspective.

The objective probability, π, of a given odds pairing was calculated as the observed proportion of winning under bets (i.e., number of winning under bets divided by total number of games for that odds pairing). Subjective probabilities, however, required additional computations. For standard lines (e.g., -110, +100), subjective probabilities, ρ, were calculated as

$$\rho = \frac{\beta_1 + 1}{2\beta_1 + \beta_1\beta_2 + 1}$$

and for double negative lines (e.g., -130, -105)

$$\rho = \frac{(1/\beta_1) + 1}{\left((1/\beta_1) + (1/\beta_2) + 2\right)}$$

To determine the significance of differences between the subjective and objective win proportions, the observed proportions were converted into a z-score as follows

$$z_l = \ (\pi - \rho_l)/[((\rho_l(1 - \rho_l))/\ n_l)]^{1/2}$$

where z_l is the computed z-score for a given odds pairing, π is the number of winning under bets, or objective win probability, ρ_l is the subjective win probability which was calculated above, and n_l is the total number of contests measured for that specific under odds line. A two-tailed test of significance was then conducted at both the 10% and 5% levels.

When a particular odds pairing within a given strategy rejected the null of market efficiency, the potential for profitability was assessed. This test was characterized by the following

$$\text{HO2}: \pi \leq \text{G}$$

$$\text{H2}: \pi > \text{G}$$

where π is the objective win probability and G is the break-even win proportion needed to achieve profitability based on the given under odds. This proportion was calculated as

$$\text{G} = \frac{\text{Amount Risked}}{\text{Amount Risked} + \text{Amount to Win}}$$

For example, given the closing under odds of (-120) and a standard wager of \$100, the break-even win proportion would be calculated as follows:

$$G = \frac{120}{120 + 100} = 54.54\%$$

When the objective win proportion, π, of a given strategy met or exceeded the break-even win proportion, a one-tailed significance test based on the calculated z-score was conducted identical to that utilized to assess market efficiency. The only difference was in the handling of ρ_l, the subjective probability. For tests of profitability, the value of ρ_l was specified as the break-even win proportion for the given odds pairing as opposed to the calculated subjective probability. This allowed for the test to appropriately assess the significance of the difference between the objective win probability and the subjective win probability assumed by the break-even win proportion.

Analyses of each strategy produced a wealth of statistics. In order to provide more interpretable conclusions, strategies were assessed based on two metrics. The first was the number of odds pairings that rejected the null of market efficiency and/or profitability. The second was actual return on investment figures, which were calculated based on those odds pairings that featured significantly profitable outcomes. This allowed for conclusions to be drawn regarding the success of a particular strategy from a purely financial perspective. The influence of heuristics was also discussed for each strategy and for the results as a whole to provide an indication of their influence on the market and its outcomes. Ultimately, the results of this research provide a foundation for understanding investor decision making in situations of risk and uncertainty through the use of well-known financial and behavioral concepts.

CHAPTER IV

RESULTS

This section presents the statistical results from the semistrong tests of efficiency for each betting strategy. The purpose of this research was to analyze the economic efficiency and profitability of the NHL totals market through the use of heuristic-based betting strategies. The strategies analyzed were comprised of common behavioral biases in an effort to provide clearer explanations for any rejections of market efficiency and/or instances of significantly positive returns. Within this context, a two-step process was utilized. First, tests of market efficiency were conducted for each betting strategy. When a particular odds pairing within a given strategy rejected the null of market efficiency, the potential for profitability was assessed. Note that in order to present more succinct results, profitability metrics were only reported in the results tables when the objective odds, π, exceeded the break-even win proportion, G, of the under closing odds being considered.

For each strategy, aggregate and individual odds pairing results were reported. It is important to note that break-even win proportion (G) and subjective probability (ρ) values were presented as sample averages in Strategy 1 and for the aggregate outcomes. The results for each strategy detail the results of the aforementioned hypotheses and are accompanied by return on investment (ROI) figures to illustrate the financial returns of each strategy. Lastly, conclusions were drawn regarding the efficiency of the NHL totals market from both theoretical and applied perspectives.

Strategy 1 – Cumulative Outcomes

There is documented evidence of bettors deriving significant entertainment value from scoring, especially in hockey where scoring is typically minimal and goals come at a premium (B. M. Woodland & L. M. Woodland, 2010). Relatedly, there is an observed under-bias in totals betting, given the psychological predisposition for bettors to wager on higher cumulative scores as opposed to lower cumulative scores (Paul & Weinbach, 2002). As a result, under wagers have been found to produce profitable results in multiple leagues. The first strategy under consideration was motivated by this evidence. Two sub-strategies were also tested that theoretically account for additional biases, which included further segmenting the sample based on the closing total and wagering on the under whenever the over odds were favored. Complete results are detailed below.

Table 4.1 illustrates the results from Strategy 1, where n is the number of games included in the strategy sample, π indicates the number of winning under wagers, and π% is the under win percentage. In this scenario, Ģ, which is the break-even win proportion, and ρ, the subjective probability, were reported as sample averages. Z-scores were assessed for significance at both the 10% and 5% levels. Recall that statistics for the null of profitability (z_profit) were only reported if the under win percentage (π%) exceeded the break-even win proportion, Ģ. Figure 4.1 displays win percentages and break-even win proportions on a seasonal basis in order to present more detailed information on the nature of this market.

Table 4.1

Strategy 1 Results

n	π	π%	G	ρ	*z_mkt eff.*	z_*profit*
6105	3104	.5084	.5302	.4587	7.7886**	

Note. * p < .1. ** p < .05. Break-even win percentage and subjective probability are calculated as sample averages.

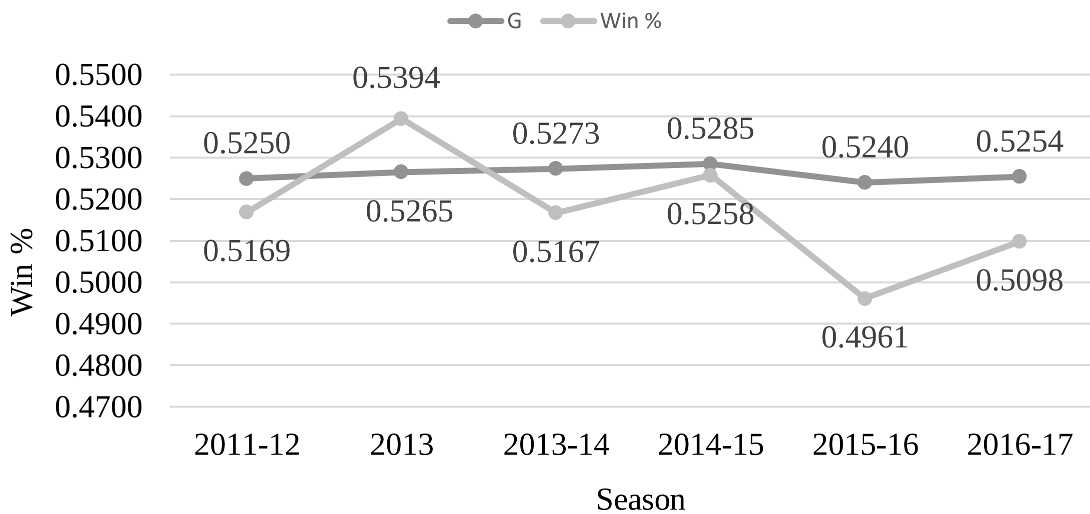

Figure 4.1. Season win percentages and average break-even win proportions.

The results for Strategy 1 demonstrate that the market rejected the null of market efficiency when all games were assessed. For reference, the null of market efficiency is rejected whenever the objective win percentage (π) is not equal to the subjective win probability (ρ). Therefore, the outcome of Strategy 1 is not uncommon given the variability of the market and the stringent nature of the test. Despite this significant measure, the win percentage did not reach a level reject the null of profitability. Even with a significant winning percentage over 50%, under bettors would not have enjoyed above average, or even marginally profitable returns. In fact, wagering $100 on the under in each game in the sample (N = 6105 games) would have resulted in a net loss of

$11,612.44 (-2% ROI), which takes into account the average commissions collected by the bookmakers. For comparison, returns in the Standard & Poors 500 (S&P 500) during this same period averaged roughly 12% ROI (Shiller, 2018).

Figure 4.1 further segments to provide insight into changes on a season-by-season basis. While the purpose of this research was to assess the market in its entirety and not on a seasonal basis, these metrics provide a more detailed look at the operational nature and relative efficiency of the market. Aside from the 2013 season (which was shortened due to a lockout from 82 to 48 games), each season featured a win percentage that fell below the average break-even win proportion needed to reject the null of profitability. Even in 2013, however, bettors would have only enjoyed a positive return of $1,713.06 (3% ROI). These results highlight the overall efficiency of this market from a financial sense. While the null of market efficiency was rejected for Strategy 1, the financial outcomes and market commissions associated with the closing totals must be considered.

Results for Strategy 1a (Table 4.2), which segmented the sample by closing totals, featured only one significant measure with no totals rejecting the null of profitability. These findings run counter to those of previous studies of the NFL, NBA, and NHL totals markets (Paul & Weinbach, 2002; Paul et al., 2004; B. M. Woodland & L. M. Woodland, 2010), in that significant deviations from market efficiency were not observed for higher totals. This finding suggests that this market has become more efficient over time, which aligns with the central premise of the EMH.

Table 4.2

Strategy 1a Results

Closing Total	*n*	*π*	*π%*	*G*	*ρ*	*z_mkt eff.*	z_*profit*
4.5	7	3	.4286	.4834	.4686	-.2121	
5	2099	989	.4712	.4918	.4617	.8746	
5.5	3913	2115	.5405	.5484	.4570	6.5856**	
6	74	39	.5270	.5224	.4759	.8814	
6.5	12	4	.3333	.5361	.4769	-.9954	

Note. * $p < .1$. ** $p < .05$. Break-even win percentage and subjective probability are calculated as sample averages for the specified closing total.

Of interest is the significant measure associated with the closing total 5.5, which appeared in 3,913 of the 6,105 contests (65%). Despite a win percentage of 54%, which did not rise to the level to reject the null of profitability, a simple strategy of wagering on the under when the total line closed at 5.5 would have resulted in a net loss of $3,812.82 (-1% ROI). Additionally, based on the fact that the average total number of goals per game during the sample equaled roughly 5.5, conventional thought might suggest that value lies in totals that fall above and below this figure. However, wagering on the under for each total that did not close at 5.5 would have resulted in a negative net loss of $7,799.62 (-4% ROI).

Strategies that featured a win percentage over 50%, or over 52.38%, may lead the average bettor to assume above-average financial returns. The findings from this strategy, however, illuminate the importance of considering commissions, even in the aggregate, when determining the financial success of a particular strategy. Figure 4.2 displays profit and loss information for Strategy 1a, which provides further clarification regarding returns for specific goal totals.

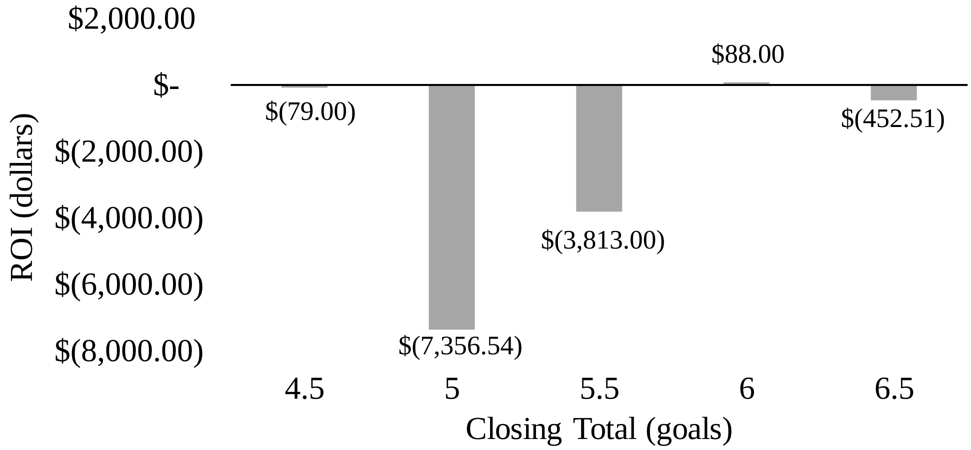

Figure 4.2. Returns on investment for Strategy 1a.

There is a documented tendency of bettors to over bet favorites, commonly referred to as the reverse favorite-longshot bias (B. M. Woodland & L. M. Woodland, 2015; L. M. Woodland & B. M. Woodland, 2003). In an inefficient market, a contrarian strategy of wagering on underdogs could result in returns that are higher than those implied by the EMH. Thus, the final test within this strategy focused on the potential for inefficiencies due to these overvaluation tendencies. Recall that in the totals market, there is no favorite or underdog in the traditional sense. Rather, these labels are reserved for the odds associated with each closing total as opposed to the teams themselves.

Table 4.3

Strategy 1b Results

n	π	π%	*G*	ρ	z_*mkt eff.*	z_*profit*
2241	1049	.4681	.4752	.4636	.4301	

Note. Break-even win percentage and subjective probability are calculated as sample averages.

Results for Strategy 1b (Table 4.3) yielded no significant measures and featured a win percentage that did not rise above 50%. Thus, a contrarian strategy of wagering against the odds (e.g., favorite-longshot bias) was not found to be profitable, with losses exceeding $2,700 (-1% ROI). Such a result would suggest that betting with the odds may be a more favorable strategy, which aligns with previous research and human tendencies to prefer favorites and the favored odds (B. M. Woodland & L. M. Woodland, 2015; L. M. Woodland & B. M. Woodland, 2010).

Strategy 2 – The Hot-Hand Fallacy

A team's success against the betting line is a common barometer for measuring team quality. It is also oftentimes used as a predictor for future performance, especially as it relates to goal scoring (Graham & Stott, 2010). A bettor may view recent outcomes against the closing total as an indicator of future results and thus wager on the continuation of such outcomes. In reality, however, these past events have no real predictive value. A simple example of this tendency may be found in the game of roulette. Signs above the roulette wheel generally show results from the last twenty spins, including number and color. If the last ten spins all landed on red, then a bettor may employ one of two strategies. Either bet on red because it is considered "hot" or take the contrarian strategy and bet on black because it is "due" (Ma, 2014).

When a bettor bases his wagers on the continuation of results, his decision is motivated by the hot-hand fallacy, or gamblers fallacy, where he assumes a correlation between past events and future outcomes. Thus, he may believe that he has an advantage in the market based on his own cognitive bias. In reality, however, each spin of the wheel or hockey game played should be viewed as an independent trial (Ma, 2014). Any previous successes, or streaks, are likely a product of statistical variance and fundamental chance (i.e., luck). Moreover, these decisions are often based on small sample sizes and fail to account for general regression concepts, which statistically invalidate their general premise.

In an inefficient market, such a bias would inflate goal totals in a way that would create favorable outcomes for the under bettor. Thus, this strategy focused on exploiting the hot-hand fallacy and the potential for overvaluation by wagering on the under for all games that featured two teams with an at or above .500-win percentage against the over closing total in their previous five games. The decision to utilize .500 as the benchmark was motivated by common sentiments that use this figure as the break-even point for determining success in a particular scenario. Since the filter for this strategy was more stringent, the cutoff for odds pairings to be included was five contests instead of twenty. The data was first considered in the aggregate and then segmented based on the closing odds.

Table 4.4

Strategy 2 Results

	Odds Pairing	*n*	*π*	*π%*	*G*	*ρ*	*z_mkt eff.*	*z_profit*
	Total[a]	1019	541	.5309	.5214	.4720	3.7068**	.5427
Under Odds Favored	(-150, 130)	7	5	.7143	.6000	.4144	1.6105	
	(-145, 125)	8	4	.5000	.5918	.4289	.4064	
	(-142, 129)	7	4	.5714	.5868	.4231	.7941	
	(-140, 120)	8	5	.6250	.5833	.4380	1.0663	
	(-139, 126)	5	3	.6000	.5816	.4321	.7580	
	(-138, 125)	7	4	.5714	.5798	.4339	.7341	
	(-137, 124)	12	5	.4167	.5781	.4358	-.1334	
	(-136, 124)	10	5	.5000	.5763	.5033	-.0206	
	(-135, 115)	12	6	.5000	.5745	.4822	.1237	
	(-135, 123)	17	8	.4706	.5745	.4355	.2917	
	(-135, 125)	3	5	.6000	.5745	.4337	.7502	
	(-133, 120)	3	5	.6000	.5708	.4433	.7053	
	(-133, 121)	13	8	.6154	.5708	.4422	1.2574	
	(-132, 120)	6	2	.3333	.5690	.4895	-.7650	
	(-131, 119)	7	4	.5714	.5671	.4460	.6674	
	(-130, 110)	12	5	.4167	.5652	.4536	-.2567	
	(-130, 118)	22	12	.5455	.5656	.4480	.9192	
	(-129, 117)	10	3	.3000	.5633	.4475	-.9380	
	(-128, 116)	16	5	.3125	.5614	.4496	-1.1020	
	(-127, 115)	21	13	.6190	.5595	.4516	1.5416	
	(-126, 114)	12	5	.4167	.5575	.4537	-.2579	
	(-125, 105)	18	9	.5000	.5556	.4646	.3012	
	(-125, 113)	15	5	.3333	.5556	.4559	-.9528	
	(-125, 115)	6	2	.3333	.5556	.5095	-.8631	
	(-124, 113)	7	4	.5714	.5536	.4570	.6079	
	(-123, 111)	4	5	.8000	.5516	.4621	1.5153	
	(-123, 112)	19	13	.6842	.5516	.4610	1.9521*	1.1625
	(-121, 110)	19	8	.4211	.5475	.4635	-.3708	
	(-120, 100)	13	8	.6154	.5455	.4783	.9897	
	(-120, 109)	26	20	.7692	.5455	.4888	2.8607**	2.2916**
	(-120, 110)	5	4	.8000	.5455	.5101	1.2966	
	(-119, 108)	15	6	.4000	.5434	.4694	-.5388	
	(-118, 107)	10	4	.4000	.5413	.5111	-.7026	
	(-117, 106)	16	7	.4375	.5392	.4725	-.2801	
	(-116, 105)	11	4	.3636	.5370	.5118	-.9833	
	(-105, -105)	52	29	.5577	.5122	.4878	1.0082	
	(-115, -105)	10	4	.4000	.5349	.4759	-.4807	
	(-115, 104)	22	8	.3636	.5349	.4782	-1.0758	
	(-114, 103)	12	7	.5833	.5327	.48047	.7134	

Table 4.4, continued

Over Odds Favored

Odds Pairing	*n*	π	π%	*G*	ρ	*z_mkt eff.*	*z_profit*
(-113, 102)	13	6	.4615	.5305	.4877	-.1884	
(-111, 101)	23	10	.4348	.5261	.4861	-.4919	
(-110, -110)	12	6	.5000	.5238	.4762	.1651	
(-110, 100)	27	11	.4074	.5238	.5116	-1.0834	
(-109, -101)	11	7	.6364	.5215	.4882	.9830	
(-108, -102)	21	13	.6190	.5192	.4881	1.2007	
(-107, -103)	11	3	.2727	.5169	.4880	-1.4281	
(-106, -104)	8	5	.6250	.5146	.4878	.7766	
(-115, -105)	9	6	.6667	.5122	.4759	1.1458	
(-106, -104)	11	5	.4545	.5098	.4879	-.2211	
(-107, -103)	8	3	.3750	.5074	.4877	-.6379	
(-108, -102)	24	14	.5833	.5050	.4881	.9336	
(-109, -101)	11	8	.7273	.5025	.4882	1.5862	
(-120, 100)	8	7	.8750	.5000	.4783	2.2464**	2.1213**
(-110, 100)	31	15	.4839	.5000	.4878	-.0438	
(-111, 101)	19	10	.5263	.4975	.4854	.3570	
(-113, 102)	18	10	.5556	.4950	.4818	.6262	
(-114, 103)	10	5	.5000	.4926	.4806	.1228	
(-115, 104)	13	7	.5385	.4902	.4771	.4431	
(-125, 105)	7	2	.2857	.4878	.5203	-1.2424	
(-116, 105)	18	9	.5000	.4878	.4748	.2145	
(-115, 105)	9	7	.7778	.4878	.4759	1.8133*	1.7404**
(-117, 106)	12	9	.7500	.4854	.4725	1.9258*	1.8337**
(-118, 107)	18	10	.5556	.4831	.4702	.7258	
(-119, 108)	13	6	.4615	.4808	.4694	-.0570	
(-120, 109)	7	4	.5714	.4785	.4673	.5522	
(-130, 110)	6	6	1.0000	.4762	.4536	2.6886**	2.5960**
(-121, 110)	21	13	.6190	.4762	.4635	1.4297	
(-120, 110)	6	5	.8333	.4762	.4646	1.8110*	1.7516**
(-123, 111)	5	2	.4000	.4739	.4602	-.2699	
(-122, 111)	8	4	.5000	.4739	.4624	.2133	
(-123, 112)	12	7	.5833	.4717	.4591	.8635	
(-125, 113)	11	8	.7273	.4695	.4559	1.8074*	1.7132**
(-124, 113)	8	4	.5000	.4695	.4589	.2333	
(-126, 114)	7	3	.4286	.4673	.4560	-.1456	
(-135, 115)	9	5	.5556	.4651	.4474	.6525	
(-127, 115)	5	3	.6000	.4651	.4516	.6666	
(-125, 115)	5	1	.2000	.4651	.4538	-1.1400	
(-129, 117)	5	3	.6000	.4608	.4475	.6859	
(-130, 118)	10	4	.4000	.4587	.4454	-.2891	
(-131, 119)	5	3	.6000	.4566	.4434	.7048	
(-133, 121)	5	2	.4000	.4525	.4422	-.1899	

Table 4.4, continued

Odds Pairing	n	π	$\pi\%$	G	ρ	*z_mkt eff.*	*z_profit*
(-135, 123)	5	2	.4000	.4484	.4355	-.1601	
(-136, 124)	5	2	.4000	.4464	.4365	-.1647	
(-138, 125)	6	4	.6667	.4444	.4306	1.1677	
(-140, 127)	5	4	.8000	.4405	.4303	1.6698*	1.6191*

Note. * $p < .1$. ** $p < .05$. Under odds cutoff was 5 contests.
[a]Break-even win percentage and subjective probability are calculated as sample averages.

When assessing the market in the aggregate, the null of market efficiency was rejected, with the under win percentage exceeding the average break-even win proportion needed to reject the null of profitability. Bettors would have enjoyed a positive return of $2,400 (2% ROI) despite a failure to reject the null of profitability. When assessing the individual odds pairings, significant deviations from market efficiency occurred in nine scenarios. Of these nine parings, all exceeded the break-even win percentage needed to reject the null of profitability, with eight yielding significant measures. The ROI for these eight pairings (n = 83) equated to a net positive return of $4,977.67 (60% ROI).

Despite this outcome, it is imperative to take into account the sample size and context when determining the relative success of Strategy 2. The 83 games that made up the eight significant odds pairings are less than 10% of the total sample. Thus, these inefficiencies may be more attributable to variability in the market and should not be considered as viable predictors of future profitability. As an aside, note that seven odds pairings that rejected the null of market efficiency when the over total was favored compared to only two when the under total was favored. Such an outcome runs counter to the results of Strategy 1b and further highlights the unpredictability of this market.

Overall, this strategy should not be considered a success. As the data suggests, the market and its players appear to appropriately consider recent performances, which thwarts the potential for significant above average returns based on a hot-hand strategy. Even though bettors would have enjoyed positive returns, the lack of significant and widespread opportunities for profitability calls into question the reliability of this strategy. This highlights the importance of assessing each game independently and provides evidence related to the efficiency of this market and the role of bookmakers. Ultimately, while investors and gamblers may choose to utilize previous statistics and trend data to inform their decisions, it is evident that solely basing decisions on correlation metrics will fail to produce substantial returns.

Strategy 3 – The Glamor Effect

Given their notoriety and popularity, glamor teams such as the Dallas Cowboys, Los Angeles Lakers, and Chicago Blackhawks are generally overbet by members of the public (B. M. Woodland & L. M. Woodland, 2015). While not concerned with teams specifically, the totals market also lends itself to the glamor effect. Even when bettors are not fans of a specific team in a given matchup, it is common for a contest between two popular teams (e.g., the Chicago Blackhawks and the Boston Bruins) to garner additional over wagers. This premise is supported by Barber and Odean (2008), who hypothesized that investors prefer attention-grabbing stocks and are more likely to invest in those that have greater notoriety. In the NHL, this creates the potential for sentiment biases to emerge for specific matchups that feature more popular teams, leading to the potential for bettors' overconfidence in high score totals. Strategy 3 focuses on this tendency for overvaluation. Table 4.5 reports the results of this strategy.

Table 4.5

Strategy 3 Results

	Odds Pairing	*n*	π	π%	*G*	ρ	*z_mkt eff.*	*z_profit*
	Total[a]	3929	2027	.5159	.5285	.4636	6.5740**	
Under Odds Favored	(-150, 136)	28	16	.5714	.6000	.4139	1.6921*	
	(-147, 134)	30	20	.6667	.5951	.4179	2.7630**	.7989
	(-145, 125)	35	20	.5714	.5918	.4289	1.7034*	
	(-145, 132)	45	25	.5556	.5918	.4214	1.8231*	
	(-143, 130)	27	15	.5556	.5885	.4249	1.3739	
	(-142, 129)	43	27	.6279	.5868	.4267	2.6685**	.5473
	(-140, 120)	27	12	.4444	.5833	.4380	.0680	
	(-140, 127)	42	21	.5000	.5833	.4303	.9128	
	(-139, 126)	24	11	.4583	.5816	.4321	.2596	
	(-138, 125)	37	22	.5946	.5798	.4339	1.9721**	.1824
	(-137, 124)	51	26	.5098	.5781	.4358	1.0664	
	(-136, 124)	33	19	.5758	.5763	.4365	1.6128	
	(-135, 115)	47	27	.5745	.5745	.4474	1.7519*	
	(-135, 123)	68	34	.5000	.5745	.4384	1.0239	
	(-134, 122)	28	14	.5000	.5726	.4403	.6366	
	(-133, 121)	58	41	.7069	.5707	.4422	4.0592**	2.0941**
	(-132, 120)	37	22	.5946	.5690	.4441	1.8423*	.3144
	(-131, 119)	58	28	.4828	.5671	.4460	.5626	
	(-130, 110)	40	21	.5250	.5652	.4573	.8600	
	(-130, 118)	94	58	.6170	.5652	.4480	3.2954**	1.0132
	(-130, 120)	21	11	.5238	.5652	.4457	.7198	
	(-129, 117)	47	29	.6170	.5633	.4500	2.3021**	.7423
	(-128, 116)	57	31	.5439	.5614	.4520	1.3943	
	(-127, 115)	54	30	.5556	.5595	.4540	1.4996	
	(-126, 114)	75	54	.7200	.5575	.4560	4.5909**	2.8334**
	(-125, 105)	47	27	.5745	.5556	.4675	1.4693	
	(-125, 113)	85	42	.4941	.5556	.4580	.6681	
	(-123, 112)	76	36	.4737	.5516	.4610	.2223	
	(-122, 111)	23	12	.5217	.5495	.4631	.5644	
	(-121, 110)	75	41	.5467	.5475	.4652	1.4151	
	(-120, 100)	49	26	.5306	.5455	.4783	.7336	
	(-120, 109)	73	35	.4795	.5455	.4673	.2083	
	(-120, 110)	30	17	.5667	.5455	.4661	1.1042	
	(-118, 107)	43	18	.4186	.5413	.4716	-.6961	
	(-117, 106)	36	19	.5278	.5392	.4738	.6489	
	(-116, 105)	57	37	.6491	.5370	.4760	2.6174**	1.6873**
	(-115, -105)	48	27	.5625	.5349	.4770	1.1862	
	(-115, 104)	73	38	.5205	.5349	.4880	.5564	
	(-115, 104)	24	10	.4167	.5349	.4892	-.7105	

Table 4.5, continued

	Odds Pairing	*n*	*π*	*π%*	*G*	*ρ*	*z_mkt eff.*	*z_profit*
	(-114, 103)	36	19	.5278	.5327	.4804	.5684	
	(-113, 102)	75	39	.5200	.5305	.4815	.6677	
	(-111, 101)	38	21	.5526	.5261	.4861	.8212	
	(-110, -110)	38	23	.6053	.5238	.4762	1.5931	
	(-110, 100)	95	38	.4000	.5238	.4884	-1.7232	
	(-109, -101)	32	16	.5000	.5215	.4907	.1052	
	(-108, -102)	58	28	.4828	.5192	.4930	-.1564	
	(-107, -103)	47	27	.5745	.5169	.4954	1.0848	
	(-106, -104)	29	15	.5172	.5146	.4977	.2107	
	(-115, -105)	45	19	.42222	.5122	.5108	-1.1891	
	(-105, -105)	149	69	.4631	.5122	.5000	-.9012	
Over Odds Favored	(-106, -104)	28	10	.3571	.5098	.4977	-1.4873	
	(-107, -103)	43	21	.4884	.5074	.4954	-.0916	
	(-108, -102)	61	32	.5246	.5050	.4930	.4931	
	(-109, -101)	33	17	.5152	.5025	.4907	.2810	
	(-120, 100)	31	14	.4516	.5000	.4783	-.2970	
	(-110, 100)	86	39	.4535	.5000	.4884	-.6472	
	(-111, 101)	43	23	.5349	.4975	.4861	.6407	
	(-113, 102)	65	29	.4462	.4950	.4827	-.5898	
	(-114, 103)	41	19	.4634	.4926	.4804	-.2183	
	(-115, 104)	68	36	.5294	.4902	.4782	.8454	
	(-125, 105)	33	19	.5758	.4878	.4675	1.2460	
	(-116, 105)	63	27	.4286	.4878	.4760	-.7535	
	(-115, 105)	20	6	.3000	.4878	.4770	-1.5847	
	(-117, 106)	45	21	.4667	.4854	.4738	-.0955	
	(-118, 107)	57	51	.8947	.4831	.4716	6.3996**	6.2186**
	(-118, 108)	42	25	.5952	.4808	.4704	1.6210	
	(-120, 109)	49	23	.4694	.4785	.4673	.0294	
	(-130, 110)	23	11	.4783	.4762	.4573	.2022	
	(-121, 110)	45	20	.4444	.4762	.4652	-.2787	
	(-122, 111)	21	9	.4286	.4739	.4641	-.3170	
	(-123, 112)	49	26	.5306	.4717	.4610	.9779	
	(-125, 113)	55	26	.4727	.4695	.4580	.2190	
	(-126, 114)	43	20	.4651	.4673	.4560	.1203	
	(-135, 115)	26	15	.5769	.4651	.4474	1.3282	
	(-127, 115)	33	10	.3030	.4651	.4540	-1.7414	
	(-128, 116)	30	12	.4000	.4630	.4520	-.5717	
	(-129, 117)	24	11	.4583	.4608	.4500	.0824	
	(-130, 118)	52	23	.4423	.4587	.4480	-.0825	
	(-131, 119)	29	13	.4483	.4566	.4460	.0242	
	(-140, 120)	22	8	.3636	.4545	.4380	-.7026	
	(-133, 121)	28	13	.4643	.4525	.4422	.2355	

Table 4.5, continued

Odds Pairing	*n*	π	$\pi\%$	*G*	ρ	*z_mkt eff.*	*z_profit*
(-135, 123)	44	26	.5909	.4484	.4384	2.0389**	3.8217**
(-140, 127)	28	15	.5357	.4405	.4303	1.1270	
(-142, 129)	21	11	.5238	.4367	.4267	.9000	

Note. * $p < .1$. ** $p < .05$. Under odds cutoff was 20 contests.
[a]Break-even win percentage and subjective probability are calculated as sample averages.

A sentiment bias for glamor teams assumes increased wagers on the over in matchups that feature at least one of these teams. This scenario creates profitable returns for the under bettor. As the results of Strategy 3 indicate, the market rejected the null of market efficiency for 16 odds pairings. Within these 16 pairings, 11 rejected the null of profitability, with five yielding significant outcomes (n = 291). A positive net gain of $6,666.54 would have resulted in an ROI of 23%. In the aggregate test, the under win percentage rejected the null of market efficiency, but failed to reject the null of profitability. Thus, employing this strategy would have resulted in a net loss of $7,028.04 (-2% ROI).

Despite the fact that glamor teams are popularized by the mainstream media and members of the general public, the data suggests that closing totals are inclusive of this information. While this strategy should not be considered a success given the lack of widespread measures of profitability, the significant measures do provide further insight into the nature of this market, which could be useful for future studies. In particular, it appears that glamor teams in the NHL do not carry the same weight as those in other professional sporting leagues (e.g., NBA, NFL). Such a finding is not surprising, given that the NHL is less popular than other mainstream sports (Gaines, 2016). Additionally, it is important to note the relatively high frequency of significant pairings when the under odds were favored. This aligns with the findings of Strategy 1b, in that wagering with the odds appears to be more financially favorable than wagering against them. Although not a consistent trend among the strategies tested thus far, it is one to consider.

Strategy 4 – Playoff Success and Recency Bias

In sport, past outcomes are used as a basis for decision making in situations of uncertainty. More specifically, recent and frequent events are more easily recalled and subsequently utilized than those that occurred further in the past and infrequently. Strategy 4 focuses on bettors' susceptibility to the availability heuristic and their potential to exclude information due to the recency bias.

In the evaluation of relative team strength, a common metric utilized is prior playoff experience. Teams who have been to the playoffs more recently are generally viewed as being stronger and thus are likely to attract more betting action. From a totals perspective, this means the potential for increased wagering on the over given the propensity for recreational bettors to correlate team success with greater goal scoring potential. Relying on this mental shortcut, however, places too great an emphasis on recent events while failing to account for the larger context. By filtering the sample to only include games that featured one or more playoff teams from the previous season, the potential for inflated goal totals based on recent successes is assessed.

Table 4.6

Strategy 4 Results

	Odds Pairing	*n*	π	π%	*G*	ρ	*z_mkt eff.*	*z_profit*
	Total[a]	4091	2105	.5144	.5279	.4647	6.3704**	
Under Odds Favored	(-150, 136)	34	14	.4118	.6000	.4139	-.0254	
	(-147, 134)	30	13	.4333	.5951	.4179	.1708	
	(-145, 125)	46	23	.5000	.5918	.4235	1.0496	
	(-145, 132)	52	22	.4231	.5918	.4214	.0245	
	(-143, 130)	34	20	.5882	.5885	.4249	1.9267*	
	(-142, 129)	50	25	.5000	.5868	.4267	1.0483	
	(-140, 120)	34	22	.6471	.5833	.4380	2.4575**	.7537
	(-140, 127)	54	32	.5926	.5833	.4303	2.4093**	.1380
	(-139, 126)	29	12	.4138	.5816	.4287	-.0149	
	(-138, 125)	39	25	.6410	.5798	.4307	2.6536**	.7742
	(-137, 127)	57	28	.4912	.5781	.4918	-.0091	
	(-136, 124)	30	15	.5000	.5763	.4336	.7342	
	(-135, 115)	44	24	.5455	.5745	.4474	1.3080	
	(-135, 123)	69	28	.4058	.5745	.4384	-.5457	
	(-134, 122)	31	16	.5161	.5726	.4403	.8507	
	(-133, 121)	65	38	.5846	.5708	.5104	1.1966	
	(-132, 120)	41	24	.5854	.5690	.4441	1.8204*	.2121
	(-131, 119)	55	28	.5091	.5671	.4434	.9804	
	(-130, 110)	47	26	.5532	.5652	.4536	1.3720	
	(-130, 118)	89	42	.4719	.5652	.4892	-.3260	
	(-130, 120)	20	13	.6500	.5652	.4457	1.8378*	.7649
	(-129, 117)	43	26	.6047	.5633	.4475	2.0726**	.5465
	(-128, 116)	68	40	.5882	.5614	.4520	2.2581**	.4459
	(-127, 115)	64	36	.5625	.5595	.4540	1.7441*	.0488
	(-126, 114)	73	45	.6164	.5575	.5114	1.7957*	
	(-125, 105)	50	27	.5400	.5556	.4646	1.0692	
	(-125, 113)	90	49	.5444	.5556	.4580	1.6457*	-.2121
	(-123, 112)	77	40	.5195	.5516	.4610	1.0300	
	(-122, 111)	25	15	.6000	.5495	.4631	1.3732	
	(-121, 110)	72	25	.3472	.5475	.4635	-1.9781	
	(-120, 100)	48	28	.5833	.5455	.4783	1.4573	
	(-120, 109)	82	42	.5122	.5455	.4673	.8150	
	(-120, 110)	22	13	.5909	.5455	.4661	1.1735	
	(-119, 108)	47	18	.3830	.5434	.4694	-1.1876	
	(-118, 107)	53	28	.5283	.5413	.4716	.8270	
	(-117, 106)	42	24	.5714	.5392	.4738	1.2674	
	(-116, 106)	60	30	.5000	.5370	.4748	.3914	

Table 4.6, continued

Over Odds Favored

Odds Pairing	*n*	*π*	*π%*	*G*	*ρ*	*z_mkt eff.*	*z_profit*
(-105, -105)	155	89	.5742	.5122	.4878	2.1517**	1.5442*
(-115, -105)	44	24	.5455	.5349	.4770	.9093	
(-115, 104)	88	51	.5795	.5349	.4782	1.9032*	.8400
(-114, 103)	40	26	.6500	.5327	.4804	2.1464**	1.4868*
(-113, 102)	73	33	.4521	.5305	.4827	-.5241	
(-111, 101)	45	24	.5333	.5261	.4861	.6346	
(-110, -110)	41	21	.5122	.5238	.4762	.4616	
(-110, 100)	103	51	.4951	.5238	.4884	.1375	
(-109, -101)	34	14	.4118	.5215	.4882	-.8918	
(-108, -102)	93	32	.3441	.5192	.4881	-2.7780	
(-107, -103)	45	27	.6000	.5169	.4880	1.5035	
(-106, -104)	36	18	.5000	.5146	.4879	.1456	
(-115, 105)	33	14	.4242	.5122	.4759	-.5944	
(-106, -104)	26	9	.3462	.5098	.4878	-1.4445	
(-107, -103)	44	22	.5000	.5074	.4877	.1628	
(-108, -102)	70	43	.6143	.5050	.4877	2.1182**	1.8296**
(-109, -101)	32	16	.5000	.5025	.4878	.1385	
(-120, 100)	31	18	.5806	.5000	.4762	1.1645	
(-110, 100)	91	50	.5495	.4878	1.1765	1.1765	
(-111, 101)	47	27	.4468	.4975	.4854	-.5291	
(-113, 102)	56	34	.6071	.4950	.4818	1.8772*	1.6777*
(-114, 103)	36	17	.4722	.4926	.4794	-.0866	
(-115, 104)	68	42	.6176	.4902	.4771	2.3207**	2.1024**
(-125, 105)	38	20	.5263	.4878	.4646	.7629	
(-116, 105)	60	25	.4167	.4878	.4748	-.9011	
(-117, 106)	43	17	.3953	.4854	.4725	-1.1028	
(-118, 107)	57	28	.4912	.4831	.4702	.3184	
(-119, 108)	43	16	.3721	.4808	.4679	-1.2594	
(-120, 109)	50	26	.5200	.4785	.4657	.7699	
(-130, 110)	25	12	.4800	.4762	.4536	.2655	
(-121, 110)	44	17	.3864	.4762	.4635	-1.0257	
(-122, 111)	21	10	.4762	.4739	.4613	.1370	
(-123, 112)	46	27	.5870	.4717	.4591	1.7400*	1.5660*
(-125, 113)	56	27	.4821	.4695	.4559	.3949	
(-124, 113)	26	17	.6538	.4695	.4570	2.0153**	1.8836**
(-126, 114)	47	23	.4894	.4673	.4537	.4906	
(-135, 115)	25	13	.5200	.4651	.4431	.7743	
(-127, 115)	38	16	.4211	.4651	.4516	-.3788	
(-128, 116)	27	10	.3704	.4630	.4496	-.8271	
(-129, 117)	25	14	.5600	.4608	.4475	1.1314	
(-130, 118)	53	28	.5283	.4587	.4454	1.2137	
(-131, 119)	34	14	.4118	.4566	.4434	-.3715	

Table 4.6, continued

Odds Pairing	*n*	π	$\pi\%$	*G*	ρ	*z_mkt eff.*	*z_profit*
(-132, 120)	21	9	.4286	.4545	.4414	-.1185	
(-133, 121)	28	11	.3929	.4525	.4394	-.4965	
(-134, 122)	20	9	.4500	.4505	.4375	.1131	
(-135, 123)	45	18	.4000	.4484	.4355	-.4804	
(-140, 127)	33	14	.4242	.4405	.4269	-.0303	
(-142, 129)	23	12	.5217	.4367	.4231	.9570	

Note. * $p < .1$. ** $p < .05$. Under odds cutoff was 20 contests.
[a]Break-even win percentage and subjective probability are calculated as sample averages.

Overestimating the influence of recent success (e.g., recency bias) is a common bias demonstrated by bettors and investors across markets. As the results shown in Table 4.6 suggest, the NHL totals market also provides support for this cognitive distortion. When compared to the other strategies tested in the present work, this approach featured the greatest number of statistical inefficiencies for individual odds pairings. Of the 85 odds pairings analyzed, 20 rejected the null for market efficiency, with all rising to a level to reject the null of profitability. Ultimately, seven of the 20 odds pairings ($n = 461$) yielded significant measures of profitability, which resulted in a positive net gain of $9,453.58 (21% ROI). Note that these significant pairings made up only 11% of the sample, which makes generalizing these findings difficult in a statistical sense. For the aggregate test, the win percentage rejected the null of market efficiency but failed the test for profitability. As a result, employing this strategy would have resulted in a net loss of $7,964.73 (-2% ROI).

As was found to be the case for the previous three strategies, the data suggests that the market appropriately considers teams' recent successes and properly prices this information. While the potential for overvaluation is present (as evidenced by the greater number of significant odds pairings), consistent returns or discernable patterns were not found. Furthermore, note the frequency of odds pairings that rejected the null of market efficiency when either the under (11) or over (8) total was favored. Unlike previous strategies where noticeable patterns emerged, this strategy did not yield such an outcome. This further supports the notion of market efficiency and that any consistent patterns or deviations are likely the result of outcome variability.

Strategy 5 – The Conjunction Fallacy

The use of statistics and data analytics has become commonplace throughout the arena of sport. Propagated by Billy Beane and his use of sabermetrics to analyze player talent, now commonly referred to as Moneyball (Lewis, 2004), analytics have become increasingly advanced and are now widely used to make decisions in situations of risk and uncertainty. In recent years, this phenomenon has trickled down from sport organizations to members of the public and more specifically, sports bettors. Successful sports bettors (e.g., sharps or wiseguys) will argue that building models based on data and analytics is imperative to long-term success, given that it is inherently difficult to gain a statistical advantage in these marketplaces. The confusion that arises for many novice bettors is the choice of which analytics to utilize as the basis for their gambling decisions. Moreover, the larger question of whether considering such information will actually lead to increased measures of profitability remains uncertain.

Strategy 5 focused on the large amount of analytical information that is available to the average bettor and the notion that more information will lead to more profitable outcomes. Commonly referred to as the conjunction fallacy, this bias exposes our desire for more information and our perception that the more information that we are able to obtain, the more likely that an event will occur. Rationally, however, the simultaneous co-occurrence of two events cannot be more than the probability of those events occurring separately. In an efficient market, closing totals reflect all available analytic information, thwarting any opportunity for sustained profitability based on the use of analytics.

Table 4.7

Strategy 5 Results

	Odds Pairing	n	π	π%	G	ρ	*z_mkt eff.*	*z_profit*
	Total	4041	2080	.5147	.5280	.4636	6.5128**	
Under Odds Favored	(-150, 130)	23	9	.3913	.6000	.4202	-.2804	
	(-150, 136)	26	12	.4615	.6000	.4139	.4931	
	(-147, 134)	21	10	.4762	.5951	.4179	.5411	
	(-145, 125)	37	21	.5676	.5918	.4289	1.7045*	-.3004
	(-145, 132)	43	19	.4419	.5918	.4214	.2718	
	(-144, 131)	20	11	.5500	.5902	.4231	1.1483	
	(-143, 130)	32	14	.4375	.5885	.4249	.1442	
	(-142, 129)	38	18	.4737	.5868	.4267	.5859	
	(-140, 120)	35	16	.4571	.5833	.4380	.2288	
	(-140, 127)	54	35	.6481	.5833	.4303	3.2339**	.9661
	(-139, 126)	22	13	.5909	.5816	.4321	1.5039	
	(-138, 125)	38	20	.5263	.5798	.4339	1.1493	
	(-137, 124)	46	21	.4565	.5781	.4358	.2840	
	(-136, 124)	29	16	.5517	.5763	.4365	1.2509	
	(-135, 115)	50	21	.4200	.5745	.4474	-.3897	
	(-135, 123)	69	38	.5507	.5745	.4384	1.8805*	
	(-134, 122)	31	14	.4516	.5726	.4381	.1520	
	(-133, 121)	65	35	.5385	.5708	.4422	1.5629	
	(-132, 120)	39	23	.5897	.5690	.4441	1.8305*	.2620
	(-131, 119)	64	35	.5469	.5671	.4460	1.6228	
	(-130, 110)	45	21	.4667	.5652	.4573	.1267	
	(-130, 118)	90	43	.4778	.5652	.4480	.5682	
	(-130, 120)	24	11	.4583	.5652	.4457	.1242	
	(-129, 117)	46	30	.6522	.5633	.4500	2.7568**	1.2151
	(-128, 116)	62	35	.5645	.5614	.4520	1.7809*	.0494
	(-127, 115)	63	32	.5079	.5595	.4540	.8606	
	(-126, 114)	75	46	.6133	.5575	.4560	2.7361**	.9731
	(-125, 105)	54	27	.5000	.5556	.4675	.0325	
	(-125, 113)	94	51	.5426	.5556	.4580	1.6451*	
	(-124, 113)	23	10	.4348	.5536	.4589	-.2321	
	(-123, 112)	81	35	.4321	.5516	.4610	-.5213	
	(-122, 111)	24	10	.4167	.5495	.4631	-.4558	
	(-121, 110)	75	31	.4133	.5475	.4652	-.8999	
	(-120, 100)	53	23	.4340	.5455	.4783	-.6456	
	(-120, 109)	89	47	.5281	.5455	.4673	1.1496	
	(-120, 110)	22	9	.4091	.5455	.4661	-.5360	

Table 4.7, continued

Odds Pairing	*n*	π	$\pi\%$	*G*	ρ	*z_mkt eff.*	*z_profit*
(-119, 108)	47	26	.5532	.5434	.4694	1.1506	
(-118, 107)	53	30	.5660	.5413	.4716	1.3773	
(-117, 106)	46	22	.4783	.5392	.4738	.0609	
(-116, 105)	58	33	.5690	.5370	.4748	1.4366	
(-115, 105)	42	20	.4762	.5349	.4892	-.1682	
(-115, 104)	80	49	.6125	.5349	.4782	2.4047**	1.3918*
(-115, 105)	23	15	.6522	.5349	.4770	1.6822*	1.1278
(-114, 103)	40	20	.5000	.5327	.4804	.2475	
(-113, 102)	69	35	.5072	.5305	.4827	.4079	
(-111, 101)	51	25	.4902	.5261	.4861	.0592	
(-110, -110)	24	41	.5854	.5238	.5000	1.0932	
(-110, 100)	97	46	.4742	.5238	.4884	-.2787	
(-109, -101)	27	13	.4815	.5215	.4907	-.0958	
(-108, -102)	62	32	.5161	.5192	.4930	.3638	
(-107, -103)	47	22	.4681	.5169	.4954	-.3739	
(-106, -104)	32	16	.5000	.5146	.4977	.0263	
(-105, -105)	158	84	.5316	.5122	.5000	.7956	
(-115, 105)	41	24	.5854	.5122	.4892	1.2323	
(-106, -104)	32	16	.5000	.5098	.4977	.0263	
(-107, -103)	40	22	.5500	.5074	.4954	.6913	
(-108, -102)	63	33	.5238	.5050	.4930	.4887	
(-109, -101)	26	14	.5385	.5025	.4907	.4871	
(-120, 100)	25	15	.6000	.5000	.4762	1.2395	
(-110, 100)	81	41	.5062	.5000	.4878	.3307	
(-111, 101)	49	31	.6327	.4975	.4854	2.0627**	1.8223*
(-113, 102)	66	33	.5000	.4950	.4818	.2959	
(-114, 103)	35	19	.5429	.4926	.4794	.7511	
(-115, 104)	58	34	.5862	.4902	.4771	1.6639*	1.1640
(-125, 105)	31	9	.2903	.4878	.4646	-1.9454	
(-116, 105)	54	17	.3148	.4878	.4748	-2.3537	
(-117, 106)	42	22	.5238	.4854	.5725	.6666	
(-118, 107)	54	25	.4630	.4831	.4702	-.1062	
(-119, 108)	31	19	.6129	.4808	.4679	1.6178	
(-120, 109)	50	26	.5200	.4785	.4657	.7699	
(-130, 110)	20	10	.5000	.4762	.4536	.4171	
(-121, 110)	46	16	.3478	.4762	.4635	-1.5729	
(-122, 111)	22	14	.6364	.4739	.4613	1.6473*	1.0361
(-123, 112)	46	28	.6087	.4717	.4591	2.0359**	1.0923
(-125, 113)	57	27	.4737	.4695	.4559	.2702	
(-124, 113)	27	15	.5556	.4695	.4570	1.0284	
(-126, 114)	40	22	.5500	.4673	.4537	1.2229	
(-135, 115)	24	15	.6250	.4651	.4431	1.7942*	.8851

Over Odds Favored

Table 4.7, continued

Odds Pairing	*n*	π	π%	*G*	ρ	*z_mkt eff.*	*z_profit*
(-127, 115)	39	16	.4103	.4651	.4516	-.5192	
(-128, 116)	23	17	.7391	.4630	.4496	2.7918**	1.9438**
(-129, 117)	20	12	.6000	.4608	.4475	1.3717	
(-130, 118)	49	26	.5306	.4587	.4454	1.1995	
(-131, 119)	25	9	.3600	.4566	.4434	-.8396	
(-140, 120)	21	10	.4762	.4545	.4331	.3988	
(-132, 120)	20	10	.5000	.4545	.4414	.5277	
(-131, 121)	22	10	.4545	.4394	.5394	.1429	
(-135, 123)	41	22	.5366	.4484	.4355	1.3054	
(-140, 127)	31	15	.4839	.4405	.4269	.6418	
(-142, 129)	20	12	.6000	.4367	.4231	1.6008	

Note. * $p < .1$. ** $p < .05$. Under odds cutoff was 20 contests.
[a]Break-even win percentage and subjective probability are calculated as sample averages.

Results for this strategy are consistent with the general premise of the conjunction fallacy, in that more information does not improve one's ability to make more accurate decisions. This strategy featured a very small number of profitable odds pairings. While the three significant outcomes yielded returns of $3,863.87 (25% ROI), the small sample size (n = 152) does not allow for statistically valid conclusions to be drawn. When assessing this strategy in the aggregate, bettors would have lost $7,903.30 (-2% ROI). Given the lack of widespread opportunities for positive returns, the evidence demonstrates that this strategy is not profitable.

The influx of data and public information available to bettors in the current marketplace may actually hinder their potential for success. Having to consider and process numerous analytic variables and metrics is an undoubtedly daunting task, even for the most experienced bettor. Strategy 5 suggests that consideration all of the available metrics may not put one on the ideal avenue for success. While this is not to suggest that bettors and investors should completely ignore all analytic data, such information should not be considered in a vacuum. Rather, it should be integrated with other forms of information (e.g., location, roster makeup, injuries, etc.) in an effort to maximize one's advantage in the marketplace. Therefore, while the conjunction fallacy may have been a factor in this particular instance, the simplistic nature of this strategy and analytics variables utilized should be considered before making definitive conclusions regarding the use of analytics in sports betting.

Conclusion

The five strategies analyzed in the present work provide a comprehensive outlook on the efficiency and profitability of this market. These results provide new and valuable insights for bettors into the nature of the NHL totals market. In the aggregate, each strategy featured a win percentage that rejected the null of market efficiency. Only one (Strategy 2) rejected the null of profitability, ultimately yielding an insignificant outcome (p = .2937). Based on these results, negative returns were common and substantial (see Figure 4.3).

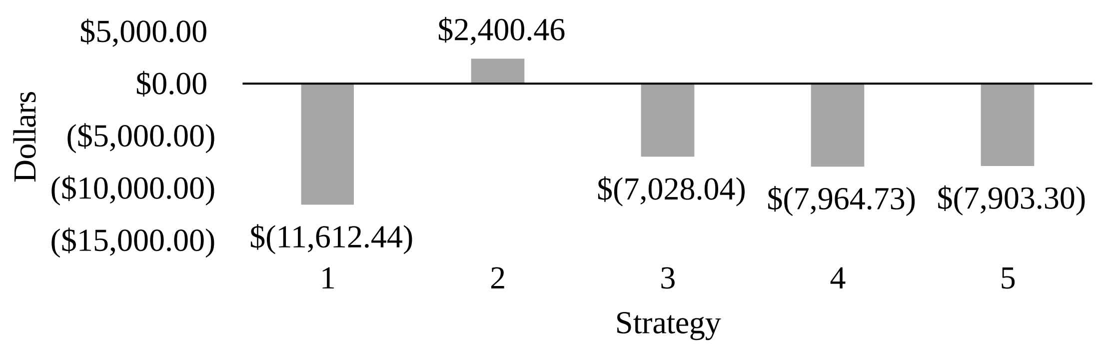

Figure 4.3. Aggregate return figures for each of the five strategies analyzed.

Similarly, individual odds pairings did not feature consistently significant outcomes and returns, which accentuates the efficient nature of the market. While the null of market efficiency had the potential to be rejected for virtually every odds pairing (due in part to the stringent nature of the test), the lack of significant outcomes is what motivated the labeling of this market as efficient. Moreover, the lack of opportunities for sustained profitability demonstrates the importance of considering the odds associated with each closing total when attempting to determine the success of a particular strategy. Failure to consider these prices would have resulted in inaccurate conclusions and would not have allowed for true profit/loss figures to be calculated.

As Figure 4.4 illustrates, only Strategy 2 produced an outcome with a net positive return of $2,820.48. Theoretically, this strategy would be considered a market anomaly, indicating that such a result is unlikely to occur again in the future. The remaining strategies lost $7,028.04, $7,544.62, and $7,802.66, respectively. Therefore, when employing all strategies simultaneously, a bettor would have lost $19,554.84 over the six seasons analyzed. This supports the concept of market efficiency because above-average returns, albeit present in one circumstance, were not widespread.

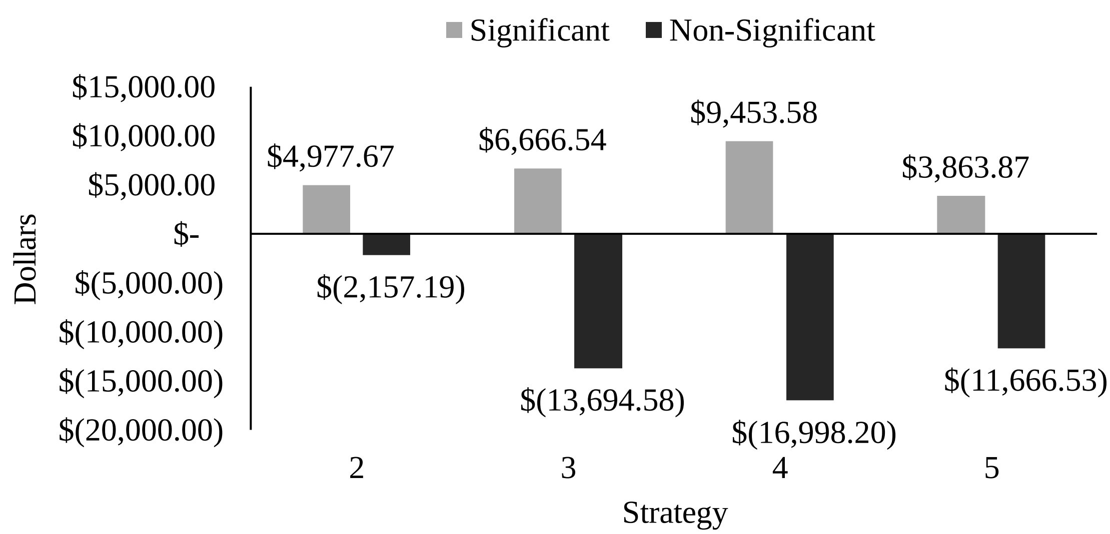

Figure 4.4. Odds pairings return figures for Strategies 2, 3, 4, and 5.[2]

[2] Strategy 1 was not included in these calculations as it only featured statistical averages and not odds-specific values.

Considering odds pairings when determining the efficiency of this market is imperative. B. M. Woodland and L. M. Woodland's (2010) previous study that found this market to be inefficient and profitable utilized a standard break-even win proportion of .5238 (52.38%), which is appropriate only for flat odds (-110, 100) structures, for their tests of profitability. Thus, their results and conclusions should be interpreted with caution. Failure to take into account these odds pairings does not properly reflect the market's variable odds structure. The results of the present study concluded that the NHL totals market was semistrong efficient, given the limited number of statistically significant deviations from market efficiency and subsequent opportunities to achieve above-average returns. This conclusion is further discussed in the following chapter.

CHAPTER V

DISCUSSION AND CONCLUSIONS

The National Hockey League totals market provides a unique setting for the testing of financial theories. In this relatively simplified context where data is readily available, theories such as the Efficient Market Hypothesis can be rigorously tested. Thus, insights may be drawn regarding the human processing of information (e.g., heuristics) and the pricing of assets (e.g., contests). Previous tests of this market and similar markets in other professional leagues have found varying degrees of inefficiency for specific total lines, especially for high totals (Paul & Weinbach, 2002; Paul et al., 2004; B. M. Woodland & L. M. Woodland, 2010). Focusing on the NHL specifically, B. M. Woodland and L. M. Woodland (2010) found that a clear under bias existed in the NHL totals market (2005-2006 to 2009-2010). However, this bias appears to have diminished over time. This was hypothesized by B. M. Woodland and L. M. Woodland (2010) and is consistent with many biases in the sports wagering and investment literature.

This paper sought to extend the literature related to market efficiency in sports wagering markets by including odds and expanding the data set. These additions allowed the present research to overcome some of the limitations of previous studies. Two notable findings will be discussed in detail in this chapter. The first is that the NHL market is most accurately characterized as semistrong efficient. This characterization holds despite the rejection of the null of market efficiency for each aggregate test, because when commissions were considered, all but one strategy yielded a negative return.

The second notable finding is the lack of influence of heuristics and heuristic-based strategies on betting outcomes. As Tversky and Kahneman (1974) note, while heuristics generally provide reliable estimates, decision making biases are common and can lead to errors in judgement and misperceptions related to probability and chance. It is important to remember that this research does not include an exhaustive exploration of every possible facet of the market. Thus, future investigations with the use of more recent data have the potential to produce new findings about the influence of heuristic-based strategies.

Efficient Market Hypothesis Discussion

The characterization of this market as largely semistrong efficient was motivated by the lack of statistically significant outcomes for analyses of efficiency and profitability. Moreover, individual odds pairings, which are crucial to consider, did not feature consistent trends or above-average returns. This supports the notion of market efficiency. Therefore, it appeared that instances of inefficiency were random with no consistent pattern among strategies. This aligns with the conclusions of Rishe (1997), who determined “that the betting market (as a whole) can be inefficient in both the short run and long run, but is efficient with respect to any particular strategy” (p. 4). Accordingly, the results of the present study indicate that bettors who employ particular strategies should expect consistent negative returns on average. Thus, despite updated information, data, and more sophisticated modeling techniques, the market aligns with the premise of the EMH.

While there are a host of potential explanations for this finding, four will be detailed as they pertain to this market specifically. The first is the nature of totals betting and the lack of attention that the NHL receives. From a media standpoint, the NHL is not a central focus of the major sports networks. Rather, attention is placed primarily on the other three major North American sports leagues (NFL, NBA, MLB), which may deter bettors from becoming involved in the NHL markets due to unfamiliarity. From a betting standpoint, totals betting is also largely ignored in the media discourse. Attention is rather placed on how teams will perform against the point spread or which team will emerge the winner of a particular matchup. Again, this may deter bettors from becoming involved in the totals market due to a lack of understanding and awareness. Moreover, recreational bettors are generally more interested in aligning their investments with a particular team, rather than an overall total, which requires attention to be given to both sides of a contest.

The lack of scoring variability and the variable odds makeup of this market may also contribute to the finding of efficiency. Aside from the MLB, the NFL and NBA feature final scores that are oftentimes much larger than those in the NHL, which averaged roughly 5.5 goals during the seasons analyzed in the present work. A central tenant of investing, whether in the stock market or otherwise, is acting when prices reach levels that suggest a statistical advantage or financial value. Such a position will undoubtedly vary from individual to individual, as each investor is subject to his or her own interpretation of the available data.

The absence of variability in scoring in the NHL, however, may limit the occurrence of value plays for bettors, especially when one considers that odds are more likely to shift than totals. For example, a bettor may find value in the following line:

Boston Bruins at Washington Capitals: 6over+110; 6under-105

However, this advantage may be eliminated once other bettors become involved in the market and force the bookmaker to raise the under odds from -105 to -125 in order to balance the wagers. This new line may then read as follows:

Boston Bruins at Washington Capitals: 6over+120; 6under-125

This shift now requires a greater investment without the same return potential. What was once a value play now simply becomes another 50/50 proposition for this particular bettor. Thus, the lack of variability in scoring and the variable odds nature of this market, which allows bookmakers to alter potential payouts, may contribute to the finding of market efficiency.

From an operational standpoint, the NHL totals market features low limits and lacks large return potential, which may thwart potential investors from becoming involved. While this may not deter the recreational bettor, professional gamblers may choose to invest their money elsewhere, thus eliminating the potential for large bets to skew the market prices away from efficient values. For example, the popular online sportsbook Bovada limits wagers on totals in the NHL to $500 per wager, the lowest of the four major North American sports. In comparison, the Bovada limit for the NFL point spread market is $5,000 per wager. In cases such as this, the influx of money from both professional and recreational bettors has a greater potential to skew lines away from efficient values.

In addition to these low limits, the lack of investor development and maturation in this market may explain the finding of market efficiency. In financial markets, investors are largely motived by wealth propositions and must heavily consider the amount of risk associated with each outcome. In betting markets, however, participants are generally recreational, operating with stakes that are relatively small in comparison. Such factors may contribute to decisions that are motivated by emotion rather than profit maximization. Therefore, given the potential that there are less players and lower financial stakes, it is likely that prices will remain largely efficient.

Heuristic Discussion

Investigating the influence of heuristics on the efficiency of the NHL totals market was a central component of this research. As is common in many investment-based fields, biases are expected to arise due to the nature of human cognitive processes. One of the fundamental challenges encountered in decision making research is how to best measure and quantify the impact of these decisions (Hastie & Kameda, 2005). The present work aimed to formulate strategies that focus on exploiting investor biases to gain a better understanding of if and when these biases may be influential. Moreover, with such information it would be possible to create more directed investment models that may provide similar insights in other markets.

Unlike previous studies (e.g., Camerer, 1989; B. M. Woodland & L. M. Woodland, 2016; L. M. Woodland & B. M. Woodland, 2015; Paul & Weinbach, 2005), the present results indicate that heuristic-based strategies do not lead to opportunities for profitability. Rather, it appears that the NHL market appropriately incorporated the information that influenced each strategy, which limited the potential for consistent and above-average returns. The only instance where a heuristic did appear to have an influence was in Strategy 5, where the results appeared to support the notion that more information is not necessarily beneficial when it comes to probabilistic judgments (e.g., the conjunction effect). It should be stated however, that the simplistic design of this strategy, which involved simply averaging advanced metrics to rank teams, may not produce truly valid and generalizable conclusions.

There are four potential explanations that may account for the lack of the impact that heuristics appear to have on this market. Given the nature of these cognitive concepts, explanations will be largely theoretical, since the heuristics proposed by Tversky & Kahneman (1974) which motivated the tested strategies are descriptive and untestable in the empirical sense (Berg & Girgerenzer, 2010; Forbes, Hudson, Skerratt, & Soufian, 2015). The first explanation has to deal with the variable odds structure associated with each closing total. In the season wins total markets where heuristics were found to have an influence, flat odds (-110, 100) are employed. Thus, the totals themselves are forced to shift since the odds remain consistent. In the NHL totals market however, the variable odds structure allows bookmakers to adjust prices without modifying totals, which aids in the elimination of profitable avenues.

For example, in a matchup between two glamor teams, the total may be inflated due to the popularity of the teams. If in fact, the amount of wagers (and dollars) was significantly higher on the over side, bookmakers could adjust the odds, not the total, to make the under price more appealing. Such an adjustment has the potential to be beneficial to the bookmaker in two ways. First, this shift assumes that new bettors would wager on the under, given the more attractive price affixed to the total. Second, the financial liability of the bookmaker becomes minimized, as the increased under wagers would aid in balancing their book. While tracking line movements such as these was beyond the scope of the present research, this shift in the odds may explain the lack of inefficient closing totals.

The second explanation posits that, on average, NHL bettors are more skilled and sophisticated than those in other leagues and betting markets. Similar to B. M. Woodland & L. M. Woodland's (2015) analysis of the NBA season win totals market, the finding of economic efficiency in the present research suggest that NHL bettors are equipped to avoid the pitfalls of heuristic-based strategies. As Reber (1996) describes, "basketball has historically attracted the most sophisticated sports bettors, folks who are more knowledgeable about the game than those who bet [on] football and baseball" (p. 309). The results of this study would suggest that NHL bettors, similar to NBA bettors, are more informed than those in the NFL. The nature of the sport and lack of widespread popularity also makes it less attractive as an investment option than the more prevalent American leagues. This is evidenced by the fact that totals and their associated odds closed at relatively efficient values on a consistent basis over the six seasons evaluated in the current study. While this claim cannot be empirically supported through solely quantitative analysis, it is aided by the results of the present study and the apparent nature of the individuals participating in the market.

The ambiguity of line pricing is another factor that should be considered. Prices in gambling markets, much like those in the stock market, are vulnerable to social influences because there are no accepted theories that definitively explain how prices are set and adjusted (Shiller, 1984, 2015). Everyday sports bettors, who make up a large portion of the gambling industry, operate with no models or very limited models built around forecasting prices and outcomes. The primary issue that arises for these individuals is how to value and quantify new information as it is introduced into the market. For example, an injury to a top goaltender will undoubtedly have an impact on the line/odds set by bookmakers. While recreational bettors will likely also consider this information, there is no objective way to know how to appropriately price such information. Is it worth a half point on the point total (e.g., 6 to 5.5), or a drastic shift in the odds (e.g., -110 [favorite] to +125 [underdog]), or both? Similar questions may be raised regarding appropriate prices for glamor team matchups and the influence of prior playoff success. The inability to objectively price this information is what may have led to the finding of economic efficiency. If bettors had this ability, heuristic-based strategies may be marginally more successful.

The final potential explanation centers on the concept of publicly available information and its inclusion in prices as a part of the EMH. Despite findings that heuristic-based strategies have produced profitable outcomes in various leagues (B. M. Woodland & L. M. Woodland, 2015, 2016; L. M. Woodland & B. M. Woodland, 2015), similar approaches were not found to be successful in the NHL totals market. This implies that once these strategies and processes become publicly available, they are subsequently exploited by bettors to a degree that eliminates their potential to yield profitable measures in the future. It is important to note that such a postulation does not suggest that these biases (e.g., failure to account for regression, recency bias, sentiment bias, etc.) are not present, but rather that that market has appropriately considered their influence. This aligns with a core tenant of the EMH, which suggests that prices are inclusive of all publicly available information to the degree that technical analysis will not permit above-average returns.

Generalizability

The generalizability of these findings to other sport and financial markets is limited. This section will focus on the theoretical framework of market efficiency and the performance of the proposed betting strategies. As it relates to the EMH, the results of the present study clearly demonstrate that this market operates efficiently. While the significant outcomes related to market efficiency may lead members of the academic community to refute the characterization of the market as efficient, practitioners are more interested in financial outcomes than theoretical conclusions. Much like other sport wagering markets, there were no opportunities for profitable returns that were sizeable enough to warrant a six-year investment commitment. The one strategy that did feature a positive outcome (Strategy 2), only netted roughly $2,800. Even for a beginning investor, such a return would not warrant further use of such a strategy.

The instances of increased ROI for predicted odds pairings can largely be explained by variability and not by predictability. Practically, it would be very difficult to accurately apply findings related to randomly occurring specific odds pairings to future seasons and other markets. Unless the profitability of a particular odds pairing continues to exist over a significant period of time (e.g., 3-5 seasons) the market would remain efficient.

The findings of this research are generalizable in the sense that they support the theory of efficient markets. Despite the consideration of advanced metrics and strategies built upon theories of heuristics, outcomes are ultimately decided by the coaches and players, both of which contain the human element and thus embody a degree of randomness that cannot be consistently predicted.

Future Research

This study examined the efficiency of the NHL totals market and the influence that heuristics had on betting outcomes. While research related to betting market efficiency is far from novel, little research has directly assessed the degree to which heuristics influence the market and its prices. This section will outline three avenues for future research to build upon these findings.

First, the influence of heuristics has only been directly studied in the season wins total market and now in the NHL totals market. Given the abundance of heuristics-based literature in the various financial and investment markets, there are clear methods to apply these concepts to other sport wagering markets. In particular, the college football betting market may feature a degree of heuristics-based inefficiency, given the magnitude and intensity of this particular fan base. Thus, strategies concerned with exploiting fan loyalty in games that feature high-profile teams may lead to profitable measures.

Second, more detailed betting strategies could be articulated that center on the wealth of publicly available metrics. This study took the simple approach of averaging advanced metrics to rank teams from year to year. For informed bettors and investors, analysis of more in-depth strategies would be appealing. In particular, the determination of whether team versus player-specific statistics are more predictive would aid in strategy and model creation. The reality is that such information is readily available, yet novices are not equipped to appropriately assess these data. While future research is likely to vary in its conclusions regarding these metrics, there is a market for such practical information that could be coupled with further tests of market efficiency.

Lastly, as is the case in financial markets, opportunities exist for new and creative tests to be conducted that are theoretically grounded and assume efficient prices. For example, the ambiguity of price setting and the value that certain information has to the betting line is largely unknown. Building a model that attempts to quantify such information, under the notion that the market operates efficiently, would be both interesting and applicable. Another potential avenue would be to explore the predictive power of advanced metrics, not in an effort to gain a statistical advantage in the market, but to better understand how such information should be processed. For example, should goaltenders be more highly valued than first-line centers? How much influence does a top-tier goaltender have on the closing total in the NHL totals market? Such questions have become more relevant in the present day marketplace and have the potential to produce applicable results.

Limitations

As with any research endeavor, this research featured limitations that should be addressed. The primary limitation lies in the assumption that sportsbook seek to balance the books as opposed to taking a vested position in the market and against bettors. Such an assumption is consistent with previous research and is necessary to allow for the calculation of subjective probabilities and for accurate conclusions to be draw. However, it would be ideal to know precisely how bookmakers operate to draw more precise conclusions. A second limitation is the small sample size associated with the various odds pairings in Strategy 2. The stringent nature of this test thwarted the potential to obtain larger samples for each pairing, which may have influenced the volume of significant outcomes. Lastly, this research included games played during lockout season of 2013 which was shortened from 82 to 48 games. Given that above average returns were observed only for this season (see Figure 4.1), there is the potential that its inclusion may have had an impact on the results of the betting outcomes.

Conclusion

Sport wagering markets have evolved and grown considerably in recent years. This rise in notoriety has created a unique line of research centered on empirical tests of market efficiency and the Efficient Market Hypothesis. To date, only one other study has analyzed the NHL totals market (B. M. Woodland & L. M. Woodland, 2010), yet it failed to account for the variable odds associated with each closing total and did not consider the potential influence of heuristics. By employing a more expansive data set and focusing specifically on exploiting bettor biases (e.g., heuristics), this research sought to provide a more detailed assessment of the NHL totals market.

Statistical tests yielded results that largely supported the EMH, in that prices appeared to accurately reflect all publicly available information, making it difficult to achieve above-average returns. While rejection of the initial hypothesis ($HO1: \pi=\rho$) was common in the aggregate, the odds-specific tests featured minimal significant outcomes. Moreover, rarely did win percentages reach a level to reject the null of profitability and even fewer produced profitable outcomes. While some might argue that rejection of HO1, to any degree, would indicate an inefficient market, such an argument is misleading from a financial perspective. In every strategy except for Strategy 2, bettors would have experienced significant financial loss, to a degree that would generally not permit the recreational bettor to sustain involvement in the market. Thus, given that this research is geared toward practical applicability, the characterization of the market as efficient was largely motivated by these financial outcomes.

A central aim of this research was to understand whether the exploitation of heuristics would lead to increased levels of profitability. As such, the strategies tested were motivated by various known cognitive biases (e.g., the recency bias, the hot-hand fallacy, the conjunction fallacy). Unlike findings for the various season wins total markets (B. M. Woodland & L. M. Woodland, 2015, 2016; L. M. Woodland & B. M. Woodland, 2015), heuristics did not appear to affect the behavior of bettors and the efficiency of this market. In fact, the identified strategies would have resulted in significant losses totaling close to $20,000. Therefore, it can be concluded that in this market both bookmakers and bettors appropriately consider the potential for these biases to create inefficient closing totals/odds.

The results of this research provide strong indication that the NHL market operates efficiently and appropriately considers the potential for biases to skew closing lines. Three explanations of these findings should be noted in particular. The first considers the variable odds nature of the market, and the fact that bookmakers can adjust prices quickly to achieve market efficiency. The second is the ambiguity in how totals/odds are set. There is no published information that quantifies certain metrics and the relative strength of particular teams. This makes the creation of tailored betting strategies difficult. Finally, the speed at which information is incorporated into the market is likely the primary influencer of these findings. When a bettor finds a profitable strategy and acts upon it, such information is quickly absorbed into the market, diminishing future potential for profitable strategies. Thus, the above-average returns of Strategy 2 will, in all likelihood, disappear in the future, given the rate at which information is processed.

Overall, this research provides further insight to the efficient nature of sport wagering markets. While findings of isolated inefficiencies are not uncommon in the literature, such outcomes rarely lead to above-average returns and invariably diminish over time. Future research should begin to focus on how prices are set and the value of certain types of information (e.g., injuries, prior playoff success). This would allow for the formulation of more informed strategies, which can then be tested against the efficient market model. As betting markets continue to grow and flourish, research related to their financial potential will remain relevant.

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