ECONOMIC COMPETITION AND THE PRODUCTION OF WINNING IN PROFESSIONAL SPORTS

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Abstract

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This dissertation includes three essays on the economics and management of professional sports with an emphasis on strategic management and quantitative methods. The first paper is a theoretical paper that provides an alternative perspective of professional sports team owners' incentive to invest in a level of talent. The second paper examines the relationship between the demand for watching games on television and attending games in person. The third paper is an application of microeconomic theory and econometrics that estimates different forms of the contest success function and develops a new empirical approach to measuring players' effectiveness.

The chapter titled "Economic Competition and Player Investment in Sports Leagues" provides an alternative perspective of professional sports teams' incentives to invest in talent based on market and ownership structures. Since territorial rights limit fans' ability to trade off between the qualities of teams that are direct substitutes, the

possibility exists that some fans will choose between indirect substitutes based on relative team qualities (e.g. winning). If this is the case, then both the market and ownership structures will affect the owner's incentive to invest in talent. The condition of cross-ownership decreases an owner's incentive to invest in talent compared to the duopoly.

The chapter titled "A Comparison of Television and Gate Demand in the National Basketball League" estimates the demand for gate attendance and television audiences in the NBA and finds that the fans who attend games in person are inherently different from fans who watch games on television. Fans who watch the games on television are more responsive to winning and do not substitute for other professional sport leagues compared to fans who attend the games in person.

The chapter titled "Contest Success Functions and Marginal Products of Talent" contributes to the literature by being one of the first papers to empirically estimate a contest success function. Although tournaments, conflicts, rent-seeking, and sporting events have been modeled with contest success functions, little empirical support exists. The contest success function is further used to determine the contribution to winning of the candidate players for the 2010 Canadian Men's Olympic Hockey Team.

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CHAPTER 1: INTRODUCTION

Since Rottenberg's (1954) seminal article spurred the development of the field of research called sports economics, winning has been recognized as an important determinant of demand. However, the market for professional sports has changed. Economic competition exists more than before. Leagues have expanded to include more teams. From 1970 to 2010 membership in Major League Baseball (MLB), the National Basketball Association (NBA), and the National Hockey League (NHL) increased from 24, 17, and 14 respectively to 30. In the absence of direct competition, this expansion has increased the amount of indirect competition from teams in competing leagues. Therefore, examining the impact of substitutability between teams in different leagues and winning is of increasing importance.

The dissertation focuses on the impact of the substitution effect between teams in different leagues and the production of winning. Some of the questions investigated are: What are the impacts of economic competition and ownership structures on team quality? Under what conditions do league policies affect the quality of teams in other leagues? How do economic competition and winning affect gate demand differently than television demand? Finally, how can the production of winning be modeled? The answers to these questions provide insights into league behavior and factors that determine demand beyond the current literature.

Economic Competition and the Effects of Fan Loyalty on Team Quality

Sports teams operate with regional monopoly. Fort and Quirk (1995) introduced a two team league model to analyze owners' incentives to invest in winning. However, the absence of direct competition has created a "gap in the chain of substitutes" introducing product dimensions into the market space. Figure 1 depicts the number of markets with at least one team from each league (MLB, NBA, and NHL). Using the number of markets with one team from each of the three leagues as a benchmark for the amount of economic competition, the number of markets with one team from each of the three leagues increased from 7 to 14. Chapter Two shows that, if fans make consumption choices based on the quality of all the teams in the market, then teams with more loyal fans will have lower quality teams.

The Effects of Cross-Ownership on Team Quality

Cross-ownership is the common ownership of teams in different leagues located in the same region. Winfree (2008) shows that teams in competing leagues are substitutes. Figure 1 also graphs the number of cross-owned firms among the markets that contain one team from each of the three leagues. As the number of markets with a team from each league increased from 7 to 14, the number of cross-owned firms increased from 2 to 9, obtaining a maximum of 11. From an owner's perspective, an important advantage of the cross-owned firm is: in solving the joint profit maximization problem, it eliminates the externalities between the teams. Therefore, the cross-owned firm mitigates the effects of economic competition. Chapter Two shows that the cross-owned firm will invest less in talent than the duopolist.

The Effects of League Policies on the Quality of Teams in Other Leagues

A considerable body of research studies the effects of these league policies on the winning percentages of teams within their own leagues. Salary caps improve competitive balance by forcing the amount that large market owners invest in talent below their profit maximizing level (Fort and Quirk (1995), Vroomam (1995)). Depending on the assumptions of the model, the effects of revenue sharing on competitive balance are different. Assuming a fixed supply of talent, Fort and Quirk (1995) show that revenue sharing results in no change in competitive balance. Assuming perfectly elastic supply of talent, Syzmanki (2004) shows that revenue sharing worsens competitive balance. In contrast to previous work, I examine how a salary cap and revenue sharing affect the quality of teams in other leagues. In this analysis, the qualities of teams in leagues are linked. Therefore, league polices can affect the quality of teams in other leagues. Chapter Two derives series of conditions in which salary caps and revenue sharing will increase or decrease the talent levels in other leagues.

The Difference of Economic Competition and Winning between Gate and Television Demand

While historical television revenue data are not widely available, it is accepted that revenues generated from television have increased. For the 2007-08 season, the NBA received $4.6 billion from league-wide contracts with ABC/ESPN and AOL/Time Warner. Although media revenue is a growing source of income for sports teams, little is known about the factors of demand for games on television. Much of the literature on the demand for sports television has focused on the substitution between watching a game on television and watching a game live. Chapter three compares the differences in the substitution effect between direct and indirect substitutes as well as the effects of winning for both television and gate demand in the NBA. The results show that fans watching television are an entirely different group than fans who attend games. Fans who watch the games on television are more price sensitive, demand more winning, and do not substitute for other professional sports, compared to fans who attend games.

The Production of Winning

A contest is a game in which players increase the probability of winning by exerting effort with the objective of obtaining a prize (Skaperdas, 1996). Although sporting events, tournaments, conflicts, and rent-seeking have been modeled with CSFs, little empirical support exists. Although the literature on CSFs is extensive, only Hwang (2009) has performed an empirical analysis. In the sports economics literature, Fort and Winfree (2009), Rascher (1987), Szymanski (2003, 2004), Szymanski and Kesenne (2004), and Kesenne (2005, 2006) have used CSFs in the modeling of leagues, but empirical analysis using sports data is absent from the literature. In Chapter 4, I use a multi-stage regression technique to estimate and compare two popular forms of the CSF, the ratio and difference forms. Results show that the ratio form of the CSF is a better fit for the data. The estimate of talent parameter in the ratio form is one. This supports the assumption made by most sports economists.

The Marginal Product of Talent

Scully (1974) was the first to estimate the marginal product of talent. Although others (Scully (1989), Zimbalist, (1992)) have extended Scully's 1974 work, none have fundamentally changed or improved the method of determining the marginal product of talent. Without imposing a model, Scully and others used season level data in their analysis. Season level data is attractive for analysis. It is easily understood because the information the data contains is smoothed out from averaging, although it still contains systematic error. In comparison, contest level data is difficult to interpret. However, by imposing a model, the systematic error contained in the data is eliminated. In Chapter 4, I use contest level data and the ratio form of the CSF to estimate the marginal product of talent for the candidate players of the 2010 Canadian Men's Olympic Hockey Team.

Dissertation Format and Content

This dissertation contains three articles. The first article (Chapter 2) contains three sections of analysis. The first section of analysis develops a two-team/two-league model of professional sports leagues. While previous literature focuses on the regional monopoly power in professional sports, the scope of this research is broader. The model is first derived using the monopoly setting. Then, the cases of economic competition and cross-ownership are analyzed and compared. A measurement of fan loyalty is derived from the model and the implications of fan loyalty on team quality are discussed. The second section of analysis models the effects that salary caps and revenue sharing have on the quality of teams in other leagues. This paper is the first in the literature to analyze the cross-league effects of league policies. The third section of analysis works through an example using functional forms.

The second article (Chapter 3) contributes to the sports economics literature by comparing the factors that contribute to gate and television demand in the NBA. Historically, gate demand has been analyzed. However, although television revenues have increased, analysis of factors that contribute to demand for fans who watch games on television is limited. To estimate demand, I use two empirical models. Each is a linear regression model. The first model includes time effects, and the second includes both time and team effects.

The third article (Chapter 4) contributes to the CSF and sports economics literatures. This paper contributes to the CSF literature by being one of the first papers to empirically estimate CSFs and provide support for a particular form. This paper contributes to the sports economics literature by using contest success function to improve on the methodology of determining the marginal product of talent. The difference and ratio forms of CSFs have been identified by researchers as popular choices to develop theoretical properties and model tournaments, conflicts, rent-seeking, and sports leagues. Furthermore, sports economists often use a simplified version of the ratio form with no empirical justification. In this article, I use a multi-stage regression to estimate the parameters of difference and ratio forms of the CSFs and then compare the forms for best fit using various criteria. Empirical estimation of the CSF places value on the inputs that contribute to winning. Therefore, I develop formulas to calculate the marginal product of talent for hockey players.

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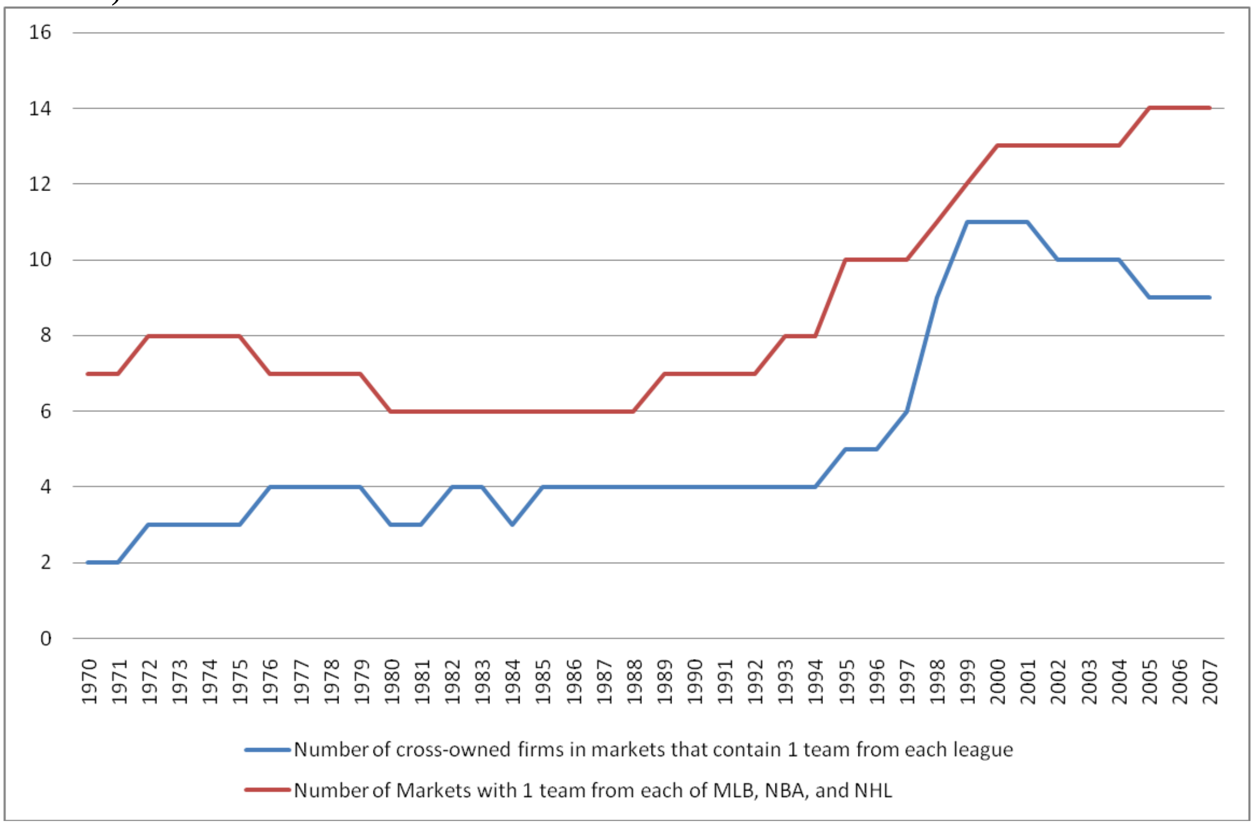
FIGURES

Figure 1. The number of markets with at least 1 team from each league (MLB, NBA, and the NHL) and number of cross-owned firms.



CHAPTER 2: ECONOMIC COMPETITION AND PLAYER INVESTMENT IN SPORTS LEAGUES

Abstract

Although most direct competition has been eliminated, indirect competition exists between teams in the same region but in different professional sports leagues. If fans make consumption choices for team products based on the quality of all teams (across sports) that are present in their region, then economic competition and ownership structure can impact the quality of teams. This article constructs a professional sports league model of an owner's incentive to invest in talent in the presence of competition from other sports leagues. Consumer preferences are allowed to vary across sports, and the winning percentages of teams in other leagues affect demand. The results suggest that more loyal fans reduce the incentive to invest in talent, cross-ownership decreases an owner's incentive to invest in talent, and that one's league policies can have an effect on the quality of teams in other leagues.

INTRODUCTION

Operating as cartels, professional sports leagues have empowered their teams with regional monopoly power. However, this absence of direct competition has created a "gap in the chain of substitutes" introducing product dimensions into the market space. It is conceivable that fans make consumption choices based on the quality of all teams (across sports) that are present in their region. In this article, I investigate how economic competition between teams in alternative sports leagues can affect quality of teams, as well as how the ownership structure can decrease team quality. The analysis is then extended to analyze the effects that revenue sharing and salary caps can have on the quality of teams in other leagues.

Higher levels of team quality, represented by winning percentage, can increase demand for the team's products (e.g. tickets, television broadcast rights, and merchandise). If fans enjoy many sports and obtain utility from rooting for a winning team, then it raises a number of research questions. How does economic competition from professional teams in other sports affect an owner's incentive to invest in talent? What are the conditions in which the winning percentages between teams act as strategic compliments or substitutes? How does owning teams in different leagues that are located in the same market (hereafter called cross-ownership) alter an owner's incentive to invest in talent? How will a salary cap and revenue sharing affect the quality of teams in other leagues? Extending the work of El Hodiri and Quirk (1971) and Quirk and El Hodiri (1974), I develop a model of an owner's incentive to invest in talent in the presence of competition from other sports leagues. I allow consumer preferences to vary across sports, and the winning percentage of teams in other leagues to affect demand. Our analysis highlights that cross-ownership decreases an owner's incentive to invest in talent and that one's league policies can have an effect on the quality of teams in other leagues.

Traditionally, sports leagues are modeled as monopolies with talent as a long-run choice variable in the team's profit maximization problem (Fort and Winfree, 2009). First, I model the monopoly case in which the owner considers the winning percent of the teams from other leagues in the market into their objective function. Depending on its own-revenue elasticity of winning, the monopolist will either invest in high or low levels of talent. This is the point where Fort (1995) and others created the two-team model, used the adding-up of winning percentage constraint to find an equilibrium winning percentage, and analyzed the effects of league policies. In contrast, I use the first-order conditions to compare the owner's incentive to invest in talent across three types of markets: monopoly, competitive, and cross-ownership.

Second, I model economic competition. Markets with multiple teams and heterogeneous fan preferences yield different results. Figure 1 depicts the number of markets with more than one major league team. Using National Hockey League (NHL), National Basketball Association (NBA), and Major League Baseball (MLB) as a benchmark, the number of markets with one team from each of the three leagues increased from 7 to 14 from 1970 to 2007. With the presence of another team in the market, I incorporate sports fans' preferences for winning in the market into the model. Overall, if fans are loyal[1], owners will invest a lower amount in talent. Consider the following example: a sports fan who likes hockey and basketball prefers to watch a

[1] Loyal fans are fans who do not readily switch between teams based on winning percentages. A formal definition is presented later in the paper.

hockey team with a winning percentage of 0.400 compared to a basketball team that has a winning percentage of 0.550. However, the same fan may prefer the basketball team if it were to have a 0.650 winning percentage, all else constant. This situation forces owners to consider fans' substitution based on the winning percentages of teams in other sports leagues into their decisions to invest in talent.

Third, I model the effects of cross-ownership and find that the cross-ownership results in lower investment in talent compared to markets in which economic competition exists. The study of cross-ownership is important because it is present in the marketplace. Table 1 shows the cross-ownership among MLB, NBA, and NHL teams. To show the relationship between the amount of indirect competition and cross-ownership, Figure 1 also graphs the number of cross-owned firms among the markets that contain one team from each of the three leagues. As the number of markets with a team from each league increased from 7 to 14, the number of cross-owned firms increased from 2 to 9, obtaining a maximum of 11 in 1999, 2000, and 2001. The correlation coefficient is 0.91. Table 2 is a summary of the cross-ownership among markets that contained at least one team from each of the three leagues from 1950 to present. Ten of the eleven markets have had ownership groups that owned teams in competing leagues. Of the regions that have contained at least one team from each league, Minneapolis is the only city that has not had cross-owned teams[2]. I summarize the progression of cross-ownership in Appendix C.

Cross-ownership has its other implications: pricing and cost efficiencies. Depending on the heterogeneity of the products, a cross-owned firm has the incentive to

[2] Minneapolis lost their NHL team to Dallas in 1993 before recently gaining back another team from expansion franchise in 2000.

increase or decrease ticket prices accordingly. Winfree (2008) shows that because of the substitutability between teams in competing leagues, cross-ownership can lengthen the duration of work-stoppages.

Consequently, the 2004-05 NHL work-stoppage resulted in a revenue increase of approximately $53 million for teams in competing leagues that were owned by a common firm. In addition, if the prices are substitutes, the increased price could allow the not otherwise successful team to become viable when it is not socially optimal, creating an overprovision of teams. Furthermore, the potential for cost saving exists if the cross-owned firm's cost function is not separable. Shared stadiums or television broadcasting might be examples of non-separable costs. To the best of the author's knowledge, the overprovision of teams and the structure of the cost functions have not been studied in the sports literature. Both are beyond the scope of this article.

Finally, I study the effects of revenue sharing and salary caps on the talent levels in other leagues. A considerable body of research studies the effects of these cross-subsidization techniques on the winning percentages of teams within their own leagues. Salary caps improve competitive balance by forcing the amount that large market owners invest in talent below their profit maximizing level (Fort and Quirk (1995), Vroomam (1995)). Depending on the assumptions of the model, the effects of revenue sharing on competitive balance are different. A fixed supply of talent results in no change to competitive balance while perfectly elastic supply of talent worsens competitive balance (Fort and Quirk (1995), Syzmanki (2004)). Kesenne (2000) shows that competitive balance can be improved with revenue sharing if revenue is a function of both the home and away teams' winning percents. In contrast to previous work, I examine how a salary cap and revenue sharing affect the quality of teams in other leagues. As a consequence, I investigate the implications of the policies of other leagues. In our analysis, leagues are inherently linked and, therefore, league polices can affect the quality of teams in other leagues. I derive a series of conditions in which salary caps and revenue sharing will increase or decrease the talent levels in other leagues.

The rest of the article proceeds as follows: section II sets up team models and compares the different incentive for owners to invest in talent across different cases: monopoly, economic competition, and cross-ownership. Section III determines the impact of league policies in alternate leagues, and section IV is an example with functional forms. Section V is the conclusion and discusses some implications.

Section II: A Two League – Two Team Model

Consider a product market in which some fans' tastes are diverse, so that there are two groups of fans: sport-specific fans and sports fans. Sport-specific fans only consume a specific sport and their purchasing decisions are based entirely on the quality of that specific team, regardless of the presence of a competing team in the market. In contrast, sports fans will potentially consume any sport that is in the market and their consumption choice depends on the quality of all of the teams in the market. I assume that teams are completely uninformed about whether any particular fan is a sport-specific fan or a sports fan. Therefore, teams only know the proportion of total fans relative to the monopoly case.

I assume there are two leagues and two teams in each league. The general model assumptions are: $\pi_{i,j}$ is the profit for the team in league $i = a$ or b (e.g. NBA, or NHL) and market $j = 1,\ 2$, or 3 (e.g. New York, Edmonton, Seattle). Market 1 is considered to be the large revenue potential market and markets 2 and 3 are small revenue potential markets. Further, for the purposes of this paper, league a is located in markets 1 and 2 and league b is located in markets 1 and 3. R is the team's revenue. Revenue is a function of its own team's winning percentage, w. Winning percentage is a function of talent or investment in talent, t, of both teams in the league The function γ (gamma) represents the proportion of total fans relative to the monopoly case. It is an open bounded set between zero and one. Gamma is a function of the winning percentages of both teams in the market[3]. Therefore, γR represents revenue normalized to the monopolist. To recap, γ is a function of the winning percentages of teams across leagues, and w is a function of talent within the same league. Fans attend either team $i = a$ or $i = b$ in market j, not both[4]. Next, I model a firm operating in three different economic markets (monopoly, duopoly, and cross-ownership) and compare the owner's incentive to invest in talent across cases.

Case 1: The Monopoly Case

With the absence of indirect competition, I normalize the monopolist's proportion of total fans to one. Therefore the monopolist's normalized revenue is derived as follows: $\gamma_{a,1}(w_{a,1}, w_{b,1})R_{a,1}(w_{a,1}) = \gamma_{a,1}(w_{a,1})R_{a,1}(w_{a,1}) = R_{a,1}(w_{a,1})$. Therefore, the profit function for team a in market 1 is,

[3] Hereafter I refer to the proportion of total fans relative to the monopoly case as the proportion of total fans.
[4] To focus on quality, I am holding quantity constant and therefore modeling profit as a function of revenue or price.

$$\pi_{a1} = R_{a1}\left(w_{a1}\right) - t_{a1} \tag{1}$$

To ensure positive but decreasing marginal revenue of investment in talent on revenue, I assume the usual conditions of,

$$\frac{\partial R_{a,1}}{\partial t_{a,1}} > 0\ ,\ \frac{\partial^2 R_{a1}}{\partial t_{a1} \partial t_{a1}} < 0 \tag{2}$$

The first order condition is,

$$\frac{\partial \pi_{a1}}{\partial t_{a1}} = \frac{\partial w_{a1}}{\partial t_{a1}} \frac{dR_{a1}}{dw_{a1}} = 1 \tag{3}$$

Equation (3) implies that the firm will invest in talent to the point where the contribution to talent on revenue equals the cost of talent. I will compare equation (3) with first-order conditions of the duopolist and cross-owned firm.

Case 2: The Duopoly Case: Economic Competition

To illustrate the effects of indirect competition, consider the market entry of an economic competitor from a different league, creating a duopoly. Consequently, the proportion of total fans is a function of the winning percentages of both teams that are present in the market. Notationally, this is represented by the function $\gamma_{a,1}(w_{a,1}, w_{b,1})$. With the presence of another team in the market, both the preferences of sport-specific fans and sports fans are incorporated into the model. No change will occur with regards to the behavior of sport-specific fans. Sport-specific fans will only choose to attend a specific sport regardless of the winning percentage of the other team in the market. The indirect competition provides a choice for sports fans. Sports fans' consumption choice depends on winning percentages of both teams in the market.

I assume that a team's own winning percentage does not decrease its proportion of the potential fan base and the other team's winning percent does not increase it; that is, $\frac{\partial \gamma_{a1}}{\partial w_{a1}} \geq 0$ and $\frac{\partial \gamma_{a1}}{\partial w_{b1}} \leq 0$. The profit function for the duopolist is

$$\pi_{a1} = \gamma_{a1}\left(w_{a1}, w_{b1}\right) R_{a1}\left(w_{a1}\right) - t_{a1} \tag{4}$$

The first order condition is,

$$\frac{\partial \pi_{a1}}{\partial t_{a1}} = \frac{\partial w_{a1}}{\partial t_{a1}} \left(\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \gamma_{a1} \frac{dR_{a1}}{dw_{a1}} \right) = 1 \tag{5}$$

The marginal revenue from winning, $\frac{dR_{a1}}{dw_{a1}}$, that was present the monopolist's first order condition is divided into two parts: $\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1}$ and $\gamma_{a1} \frac{dR_{a1}}{dw_{a1}}$. The product $\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1}$ is the revenue gained from the additional fans (both sports fans and sport-specific fans) that attend the game due to a one-unit increase in the team's own winning percentage, holding the effects of winning on revenue constant. The product $\gamma_{a1} \frac{dR_{a1}}{dw_{a1}}$ is the additional normalized revenue generated from a one-unit increase in winning percentage, holding the effects of winning on the proportion of total fans constant. The sum of the two products, $\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \gamma_{a1} \frac{dR_{a1}}{dw_{a1}}$, represents a more flexible form of the marginal revenue than the monopolist's. If $\gamma = 1$ and $\frac{\partial \gamma_{a1}}{\partial w_{a1}} = 0$ then equation (5) is equivalent to equation (3). This is the assumption made by other researchers. The assumption implies that winning does not cause an increase in the proportion of total fans and the market consisted of only sport a specific fans. This does not imply that there cannot be another sport b in the market. Rather there are simply no fans of sport a and sport b. If $\gamma = 0$, it implies that the market consists of only sport b specific fans, leaving team a with no potential fan base. For any $\gamma < 1$, the proportion of total fans has decreased because some sports fans are attending sport b. An example of this might be if fans substitute their season tickets for the existing team with season tickets of the economic competitor entering the market.

The Effects of Fan Loyalty on Team Quality

I begin my analysis by introducing a definition of loyalty from the marketing literature. Generally, loyalty is defined as repeat purchasing frequency or same-brand purchasing (Oliver, 1999). Recall, $\frac{\partial \gamma_{a1}}{\partial w_{a1}}$ represents the increase in the proportion of total fans from a one-unit increase in winning percentage. Therefore high (low) values of $\frac{\partial \gamma_{a1}}{\partial w_{a1}}$ imply sports fans are sensitive (insensitive) to the winning percentage of team a. Therefore, greater (lesser) values of $\frac{\partial \gamma_{a1}}{\partial w_{a1}}$ imply fans are less (more) loyal. I summarize the effects of fan loyalty on team quality in the following proposition.

Proposition 1: If fans are more loyal fans, then owners will invest less in talent.

Proof: Directly from equation (5).

The Effects of Economics Competition on Team Quality

To analyze the effect of economic competition, I compare equation (5) with equation (3). If $\frac{\partial \gamma_{a1}}{\partial w_{a1}} = 0$, then the proportion of total fans is not sensitive to increases in team $a's$ winning percentage and equation (3) simplifies to

$$\gamma_{a1} \frac{dR_{a1}}{dw_{a1}} \frac{\partial w_{a1}}{\partial t_{a1}} = 1 \qquad (6).$$

If in addition to $\frac{\partial \gamma_{a1}}{\partial w_{a1}} = 0$, $\gamma < 1$, equation (6) is less than equation (3), showing that the team will invest less in talent compared to the monopoly case. This is because the competing team makes the potential fan base smaller by reducing their effect population. However, if $\frac{\partial \gamma_{a1}}{\partial w_{a1}} > 0$, then the proportion to total fans is sensitive to team $a's$ winning percentage. Therefore the duopolist's level of investment in talent compared to the monopolist is ambiguous. I summarize the relationship with the following proposition.

Proposition 2: A duopolist owner will invest more in talent compared to a monopolist if the normalized revenue from a 1% increase in winning on the proportion of fans is greater than the reduction in revenue compared to the monopolist from a 1% increase in winning on revenue due to the smaller fan base.

$$\gamma_{a1} R_{a1} \varepsilon_{\gamma,w} > \left(1 - \gamma_{a1}\right) R_{a1} \varepsilon_{r,w} \qquad (7)$$

Proof: See Appendix A

The function $\varepsilon_{\gamma,w}$ is the winning percentage elasticity of the proportion of fans and $\varepsilon_{r,w}$ is the winning percentage elasticity of revenue. Since γ represents the proportion of fans relative to the monopoly case, $(1-\gamma)$ represents the reduction in the proportion due to the team that entered the market[56]. The left hand side (LHS) of equation (7) is the increase in the normalized revenue from a 1% increase in winning on the proportion of fans. The right hand side (RHS) of equation (7) is the reduction in revenue compared to the monopolist from a 1% increase in winning on revenue due to the smaller fan base. It is useful to think of γR and $(1-\gamma)R$ as weights representing the importance of the respected elasticity.

If the team entering the market altered the fan base in such a way that the fan base was evenly split, then $\gamma = .5$ and equation (7) simplifies to $\varepsilon_{\gamma,w} > \varepsilon_{r,w}$. This implies that the duopolist would invest more into talent if the team can gain more fans by winning than the additional revenue gained from that win. This is because the marginal revenue of winning is less for the duopolist than the monopolist due to the small fan base, holding the effect of winning on the proportion of fans constant. Further, less loyal fans (high values of $\varepsilon_{\gamma,w}$) result in the condition equation (7) to be more easily satisfied, resulting in greater investment in talent compared to the monopolist. However, if the winning elasticity of revenue $(\varepsilon_{r,w})$ is high, the condition in equation (7) will be less easily satisfied because the increases in winning percentage will result in the monopolist

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[5] Although R_{a1}'s divide out they are included to make easier comparisons later in the paper.

[6] $\varepsilon_{\gamma,w} = \frac{\partial \gamma_{a1}}{\partial w_{a1}} \frac{w_{a1}}{\gamma_{a1}}$ and $\varepsilon_{r,w} = \frac{\partial R_{a1}}{\partial w_{a1}} \frac{w_{a1}}{R_{a1}}$

gaining more revenue than the duopolist by the factor equivalent to the reduction in total fans, $(1-\gamma_{a1})$.

The Effects of Strategic Competition on Team Quality

Once a duopoly is established, teams have the opportunity to make strategic investments in talent. I take the approach outlined by Dixit (1987) with teams choosing levels of talent without pre-commitment. The strategic effect of talent on the changes in the other team's (team b) talent is determined by further differentiating equation (5) as follows,

$$\frac{\partial^2 \pi_{a1}}{\partial t_{a1}\partial t_{b1}} = \frac{\partial w_{a1}}{\partial t_{a1}}\frac{\partial w_{b1}}{\partial t_{b1}}\left(\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}R_{a1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}}\right) \tag{8}$$

The sign of equation (8) is ambiguous. Equation (8) introduces a new term, $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}$, the strategic effect of winning percentages on the proportion of fans. Little can be said about the sign of magnitude of $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}$ without a functional form[7][8]. The product $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}R_{a1}$, represents the increase or decrease in revenue due to strategic effects of

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[7] If the logistic form were imposed on $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}$ then, $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}} > 0$ if and only if $f_{a,1} > f_{b,1}$. See the non-symmetric case by Dixit (1987) for a graphical representation of the strategic effects. Here the logistic function is specified as $\gamma_{a,1} = \frac{f(w_{a,1})}{f(w_{a,1}) + f(w_{b.1})}$ and $\frac{d^2\gamma_{a,1}}{dw_{a,1}dw_{b,1}} = \frac{f'_{a,1} f'_{b,1}(f_{a,1} - f_{b,1})}{(f_{a,1} + f_{b,1})^3}$

[8] The logistic function is a natural choice for a discrete model (see McFadden, 1973) and is used extensively in the contest theory literature by Rosen (1986), Mortensen (1982), Tullock (1980), Hirshlefer (1989), Skaperdas (1996). It has been used in the sports economics literature to models contest by Rasher (1997), (Szymanski 2003, 2004), Szymanski and Kesenne (2004), Kesenne (2005, 2006), and Mongeon (2009).

winning percentage on proportion of fans. The product $\frac{\partial \gamma_{a1}}{\partial w_{b1}} \frac{dR_{a1}}{dw_{a1}}$ represents the reduction in marginal revenue or winning percentage from the loss of one unit of fans from the winning percentage of the other team in the market. I summarize the findings with the following proposition.

Proposition 3: If the increase in revenue from the strategic effect of winning percentage on the proportion of fans is greater, the reduction in marginal revenue of winning percentage from the marginal decrease of fans from the winning percentage of the other team in the market. Otherwise, talent acts as strategic substitutes.

Proof: See Appendix A

The two-league two-team framework introduces an indirect effect. The indirect effect can be described as follows: changes in the investment of talent of team 2 in league b will affect the winning percent of team 1 in league b, which, in turn, will affect the revenue of team 1 league a. A marginal increase in talent of team 2 in league b affects team 1 in league a in the following way,

$$\frac{\partial^2 \pi_{a1}}{\partial t_{a1} \partial t_{b2}} = \frac{\partial w_{a1}}{\partial t_{a1}} \frac{\partial w_{b1}}{\partial t_{b2}} \left(\frac{\partial^2 \gamma_{a1}}{\partial w_{a1} \partial w_{b1}} R_{a1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}} \frac{dR_{a1}}{dw_{a1}} \right) \tag{9}$$

Equation (9) has one term that is different than equation (8), $\frac{\partial w_{b1}}{\partial t_{b2}}$, which is negative compared to positive in equation (8). Therefore, the condition for strategic complements is the exact opposite as the condition in equation (8). A proposition summarizing the results for equation (9) would be the exact opposite of proposition 3. Therefore, a new proposition is not included.

Case 4: Cross-ownership

As stated, cross-ownership is the common ownership among competing teams located in the same region. The effect of cross-ownership on team quality is examined next. The profit function for a cross-owned firm is,

$$\pi_{b1b1} = \gamma_{a1t}\left(w_{a1t}, w_{b1t}\right) R_{a1t}\left(w_{a1t}\right) - t_{a1t} + \gamma_{b1t}\left(w_{a1t}, w_{b1t}\right) R_{b1t}\left(w_{b1t}\right) - t_{b1t} \qquad (10)$$

The revenue and cost of talent of team b is included in the profit function. The first order condition for team a is[9],

$$\frac{\partial \pi_{a1b1}}{\partial t_{a1}} = \frac{\partial w_{a1}}{\partial t_{a1}}\left(\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \gamma_{a1}\frac{dR_{a1}}{dw_{a1}} + \frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1}\right) = 1 \qquad (11)$$

The marginal revenue of winning is further separated to include an additional term,

$\frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1}$.

The Effects of Cross-Ownership on Team Quality

An important advantage of the cross-owned firm is: in solving the joint profit maximization problem, it eliminates the externalities between the teams. Assuming that the teams are substitutes, then $\frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1}$ is negative. This term captures the reduction in the other team that it owns revenue from the decrease in proportion of fans due to the marginal increase in winning percentage from team a. Therefore, the cross-owned firm

[9] There exists a corresponding first order condition for team b.

mitigates the effects of economic competition. For the similar reason as the duopolist $\left(\frac{\partial \gamma_{a1}}{\partial w_{a1}} > 0\right)$, the cross-owned firm's level of talent compared to the monopolist is ambiguous. I summarize the relationships with the following propositions.

Proposition 4: The cross-owned firm will invest less in talent than the duopolist.

Proof: Equation (11) is less than equation (5) by the amount of $\frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1}$.

Proposition 5: The cross-owned firm will invest more in talent compared to monopolist if the normalized revenue from a 1% increase in winning on the proportion of fans is greater than the reduction in revenue compared to the monopolist from a 1% increase in winning on revenue due to the smaller fan base less the reduction in the other team that it owns normalize revenue due to the decrease in the proportion of fans from a 1% increase in its own winning percentage.

$$\gamma_{a1} R_{a1} \varepsilon_{\gamma_{a1}, w_{a1}} > \left(1 - \gamma_{a1}\right) R_{a1} \varepsilon_{R_{a1}, w_{a1}} - \gamma_{b1} R_{b1} \varepsilon_{\gamma_{b1}, w_{a1}} \tag{12}$$

Proof: See Appendix A.

Since $\varepsilon_{\gamma_{b1}, w_{a1}} < 0$, the final product $\left(\gamma_{b1} R_{b1} \varepsilon_{\gamma_{b1}, w_{a1}}\right)$ is less than zero. The final product represents the cross-owned firm's reduction in normalized revenue due to the decrease in the proportion of fans from a 1% increase in its own winning percentage. If any of the terms in the final product are zero, equation (12) simplifies to equation (7) resulting in the same condition as the duopolist. Assuming the cross elasticity of winning on the proportion of fans is negative, the entire RHS in equation (12) is greater than in the

RHS in equation (7), making equation (12) more difficult to satisfy than equation (7). The condition is more difficult to satisfy because the cross-owned firm invests less in talent than the duopolist. The more (less) sensitive the proportion of fans are to the winning percentage of other teams in the market, the less the cross-owned firm will invest in talent and the more (less) the cross-owned firm will invest in talent compared to the monopolist. In addition, the greater team $b's$ normalized revenue is to team $a's$, the less (more) the cross-owned firm will invest in talent for team a.

Section III: The Impact of League Policies on Quality of Teams in Other Leagues

Section II shows that since the winning percentages of teams in other leagues is in the owner's objective function, talent levels across leagues are linked. This makes the study of how league policies can affect the quality of teams in other leagues important. The purpose of this section is to determine the conditions under which league policies affect other leagues' talent levels.

When the NHL first introduced the salary cap in 2005-06, teams were forced to keep salaries under \$39 million. That amount rose to \$44 million the following season and increased to \$50.3 million in 2007-08. The salary cap for 2009-10 is \$56.8 million, up just \$100,000 from \$56.7 million in 2008-09 (NHL.com). Does the salary cap that the NHL implemented after the 2004-05 lockout affect the quality of teams in the NBA? Or similarly, do changes in the NHL salary cap affect the quality of the teams in the NBA? Therefore, I analyze this question by determining the effects of league policies on other leagues' investment in talent levels with strategic effects. As the NHL increased its salary cap year after year, some of the teams that were previously constrained by spending may choose to increase their investment in talent. As investment in talent increases the quality of teams will increase. With the increased quality of NHL teams, the quality of NBA teams that are located in the same regions will be affected[10]. This is outlined in section II.

The Effects of Salary Caps on the Quality of Teams in Other Leagues

In this context, a salary cap is a limit on the investment in talent.[11] To analyze the effects of a salary cap on the quality of teams in other leagues, I assume that a salary cap is present in a league and determine the impact of a marginal change in the salary cap. The impact from implementing a new salary cap into a league can be deduced from this analysis.

The following three cases exist when analyzing a salary cap. Of the three cases, only the third case will result in cross-league effects.

1. The salary cap is not binding on any team. This scenario is trivial and not considered.
2. The salary cap is binding on both teams in the same league (assume the two-team league framework). This scenario is not considered. In this case, both teams are expected to win half of their games[12]. If the cap is binding on both teams, then there is no effect on winning percentages from a marginal change in a cap, and therefore no effect on the quality of teams in other leagues.

[10] The reverse scenario exists as well if the salary cap were to decrease.
[11] Investment in talent can be very broad and represent such things as payroll or developments. For simplicity, I assume that the cap is on investment in talent, but typically a cap is on payroll. If the cap is not on the total investment in talent it will have a mitigating effect.
[12] I assume the contest success function is the same for both teams.

3. The salary cap is only binding on the large market team. This scenario is considered. In this case, the salary cap will affect the quality of both teams in its league as well as the quality of teams in other leagues. The effect of the salary cap on the quality of teams in the other leagues is determined by analyzing the strategic effects of changes in talent.

Changes in a binding effect of a salary cap on an NHL team will affect the talent levels of NBA teams in the following two ways: (1) the strategic effect on the large market team in the NBA, (2) the effect on the small market team in the NBA from the adding up constraint from the change in the winning percent of the NBA team in the large market.

Assuming team 1 is the large market team, then the mathematical representation of the binding cap is: $\frac{dt_{b1}}{dCAP} = 1$. Therefore, the marginal effect of a salary cap on a team in a different league located in the large market is,

$$\frac{d^2\pi_{a1}}{dt_{a1}dCAP} = \frac{\partial^2\pi_{a1}}{\partial t_{a1}\partial t_{b1}}\frac{dt_{b1}}{dCAP} = \frac{\partial w_{a1}}{\partial t_{a1}}\frac{\partial w_{b1}}{\partial t_{b1}}\left(\frac{\partial^2\gamma_{a1}}{\partial w_{a1}\partial w_{b1}}R_{a1} + \frac{\partial\gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}}\right) \tag{13}$$

Therefore, the salary cap will affect the winning percentage of large market teams in other leagues. Equation (13) is the same as equation (8). As explained in proposition 3, the salary cap will act as strategic complements if the revenue gained from the increase in fans is greater than the reduction in marginal revenue from the marginal increase in the other team's winning percentage.

Second, although the salary cap is not binding in the small market team, the indirect effect of changes in the equilibrium (from the adding up constraint) of the league can affect the winning percentage of small market teams in other leagues. This results in a strategic effect in the small market team. The mathematical representation of this is $\frac{dt_{b3}}{dCAP} < 0$. Therefore, the marginal effect on profits of a salary cap on a small market team in a different league is,

$$\frac{d^2\pi_{a2}}{dt_{a2}dCAP} = \frac{\partial^2\pi_{a2}}{\partial t_{a2}\partial t_{b3}}\frac{dt_{b3}}{dCAP} = \frac{dt_{b3}}{dCAP}\frac{\partial w_{a2}}{\partial t_{a2}}\frac{\partial w_{b3}}{\partial t_{b3}}\left(\frac{\partial^2\gamma_{a2}}{\partial w_{a2}\partial w_{b3}}R_{a2} + \frac{\partial\gamma_{a2}}{\partial w_{b3}}\frac{dR_{a2}}{dw_{a2}}\right) \quad (14)$$

Equation (4) has the same sign as the condition in equation (9). The magnitude of the strategic effect is different than equation (9).

The Effects of Revenue Sharing on the Quality of Teams in Other Leagues

The result that revenue sharing reduces the incentive to invest in talent for all teams within a league is well established.[13] However, the effect of revenue sharing on competing leagues is yet to be explored. Similar to the analysis performed on salary caps, the analysis is performed through the use of strategic effects. First, the impact of revenue sharing on its own team's winning percentages is determined and then the strategic effect of changes in winning percent on competing leagues is analyzed.

The impact of revenue sharing on its own team's winning percentage is determined in the following way. Suppose that league b has a revenue sharing policy. The profit functions for the two teams in league b are,

[13] Both Szymanski (2004) and Fort (1995) show this result for talent incentives although Szymanski's models show that competitive balance deteriorates while Fort's show that competitive balance is invariant to revenue sharing.

$$\pi_{b1t} = \alpha\gamma_{b1t}\left(w_{b1t}, w_{a1t}\right)R_{b1t}\left(w_{b1t}\right) + \left(1-\alpha\right)R_{b3t}\left(w_{b3t}\right) - t_{b1t} \quad (15)$$

[14]

and

$$\pi_{b3t} = \left(1-\alpha\right)\gamma_{b1t}\left(w_{b1t}, w_{a1t}\right)R_{b3t}\left(w_{b1t}\right) + \alpha R_{b3t}\left(w_{b3t}\right) - t_{b3t} \quad (16)$$

where $\alpha \in (1/2, 1)$ is the proportion of an owner's revenue that is retained by the owner from home matches and pays $1-\alpha$ to their opponents. The first order conditions are,

$$\frac{\partial \pi_{b1}}{\partial t_{b1}} = \alpha \frac{\partial w_{b1}}{\partial t_{b1}}\left(\frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1} + \gamma_{b1}\frac{dR_{b1}}{dw_{b1}}\right) + \left(1-\alpha\right)\frac{dR_{b3}}{dw_{b3}}\frac{\partial w_{b3}}{\partial t_{b1}} - 1 = 0 \quad (17)$$

and

$$\frac{\partial \pi_{b3}}{\partial t_{b3}} = \left(1-\alpha\right)\frac{\partial w_{b1}}{\partial t_{b3}}\left(\frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1} + \gamma_{b1}\frac{dR_{b1}}{dw_{b1}}\right) + \alpha\frac{dR_{b3}}{dw_{b3}}\frac{\partial w_{b3}}{\partial t_{b3}} - 1 = 0 \quad (18)$$

Given that in a two-team league model, $\frac{\partial w_{b1}}{\partial t_{b1}} = -\frac{\partial w_{b3}}{\partial t_{b1}}$, the following equilibrium condition is obtained.

$$\left(\gamma_{b1}\frac{dR_{b1}}{dw_{b1}} + \frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1}\right)\left(\alpha\frac{\partial w_{b1}}{\partial t_{b1}} + \left(1-\alpha\right)\frac{\partial w_{b3}}{\partial t_{b3}}\right) = \frac{dR_{b3}}{dw_{b3}}\left(\alpha\frac{\partial w_{b3}}{\partial t_{b3}} + \left(1-\alpha\right)\frac{\partial w_{b1}}{\partial t_{b1}}\right) \quad (19)$$

As previously discussed in Section II (specifically equation (5)), the first term in (19) is the duopolist's marginal revenue of winning. Therefore, if I denote $\frac{dTR_{b1}}{dw_{b1}} = \frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1} + \gamma_{b1}\frac{dR_{b1}}{dw_{b1}}$ then equation (19) can be written as,

$$\frac{dTR_{b1}}{dw_{b1}}\left(\alpha\frac{\partial w_{b1}}{\partial t_{b1}} + \left(1-\alpha\right)\frac{\partial w_{b3}}{\partial t_{b3}}\right) = \frac{dR_{b3}}{dw_{b3}}\left(\alpha\frac{\partial w_{b3}}{\partial t_{b3}} + \left(1-\alpha\right)\frac{\partial w_{b1}}{\partial t_{b1}}\right) \quad (20).$$

[14] For simplicity, the γ function is not used for the team in league b although they might have a similar profit function as the other team in the same market. The results are not changed with a similar γ function.

Equation (20) represents the equilibrium condition for the winning percent in the two-team league. If team 1 is the large market team, then decreasing returns to productivity implies that $\frac{\partial w_{b1}}{\partial t_{b1}} < \frac{\partial w_{b3}}{\partial t_{b3}}$. Therefore, an increase in revenue sharing (a decrease in α) results in $\frac{dTR_{b1}}{dw_{b1}}\left(\alpha \frac{\partial w_{b1}}{\partial t_{b1}} + (1-\alpha)\frac{\partial w_{b3}}{\partial t_{b3}}\right) > \frac{dR_{b3}}{dw_{b3}}\left(\alpha \frac{\partial w_{b3}}{\partial t_{b3}} + (1-\alpha)\frac{\partial w_{b1}}{\partial t_{b1}}\right)$. Given diminishing returns to talent on revenues, an increase (decrease) in talent for the large (small) market team will make the LHS (RHS) smaller (larger). Consequently, the large market team will improve relative to the small market team[15].

Next, the effects of revenue sharing on the quality of teams in other leagues is determined through strategic effects in the following way. If teams $a1$ and $b1$ are in the large market, then $\frac{dw_{b1}}{d\alpha} < 0$, implying that revenue sharing in league b will increase the winning percentage for team $b1$. Therefore, revenue sharing in league b will have the same qualitative effect on the large market team as an increase in talent of team $b1$; which is the same condition as in equation (8). Revenue sharing in league b will have the same qualitative effect on the small market team the same as the condition in equation (9). Proposition 3 summarizes the results in terms of revenues.

The Effects of Revenue Sharing with Cross-Ownership on the Quality of Teams in Other Leagues

Since revenue sharing affects the quality of teams in other leagues, possible implications of revenue sharing on the cross-owned team exist. There are both direct and

[15] Syzmanski (2004) has a similar conclusion using functional forms.

strategic effects affecting the team quality. If revenue sharing exists in league b , then the corresponding profit function for the cross-owned team is given by,

$$\pi_{a1t,b1t} = \gamma_{a1t}\left(w_{a1t}, w_{b1t}\right) R_{a1t}\left(w_{a1t}\right) - t_{a1t} + \alpha\gamma_{b1t}\left(w_{b1t}, w_{a1t}\right) R_{b1t}\left(w_{b1t}\right) + \left(1-\alpha\right) R_{b3t}\left(w_{b3t}\right) - t_{b1t} \qquad (21)$$

The first order condition for team a is given by,

$$\frac{\partial \pi_{a1,b1}}{\partial t_{a1}} = \frac{\partial w_{a1}}{\partial t_{a1}}\left(\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \gamma_{a1}\frac{dR_{a1}}{dw_{a1}} + \alpha\frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1}\right) = 1 \qquad (22)$$

The direct effect of revenue sharing is derived by comparing the first order conditions of the cross-owned firm with (equation (22)) and without (equation (11)) revenue sharing. The reduction in revenue team $b1$ due to an increase in talent from $a1$ is smaller the greater the amount of revenue sharing. I summarize the results with the following proposition.

Proposition 6: Revenue sharing directly mitigates some of the effects of cross-ownership resulting in less of a reduction in the quality of teams.

Proof: Since $\frac{\partial \gamma_{b1}}{\partial w_{a1}} < 0$ *and* $\alpha \in \left(0.5, 1\right)$ *equation (22) is greater than (11) by the amount of* $\left(1-\alpha\right)\frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1}$.

Revenue sharing also a strategic effect by altering the quality of the team in the other market, the cross-owned team, by affecting the team's marginal revenue in the following way

$$\frac{\partial^2 \pi_{a1,b1}}{\partial t_{a1}\partial \alpha} = \frac{\partial w_{a1}}{\partial t_{a1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b3}}\frac{dt_{b3}}{d\alpha}\right)$$
$$\left[\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}} R_{a1} + \alpha \frac{\partial^2 \gamma_{b1}}{\partial w_{a1}\partial w_{b1}} R_{b1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}} + \alpha \frac{\partial \gamma_{b1}}{\partial w_{a1}}\frac{dR_{b1}}{dw_{b1}}\right] \quad (23)$$

The term $\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b3}}\frac{dt_{b3}}{d\alpha}$ is the effect of revenue sharing on the talent levels of both teams in league b. Continuing to assume team 1 is the large market team, then $\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b3}}\frac{dt_{b3}}{d\alpha} < 0$. The term in the square brackets is an expanded form of the bracket portion of equation (8) and equation (9). It includes the effects on revenue of the other team that it owns weighted by the revenue sharing factor. The terms $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}} R_{a1} + \alpha \frac{\partial^2 \gamma_{b1}}{\partial w_{a1}\partial w_{b1}} R_{b1}$ represent increase or decrease in revenue due to the strategic effect of winning percentages on the proportion of fans of each team. The terms $\frac{\partial \gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}} + \alpha \frac{\partial \gamma_{b1}}{\partial w_{a1}}\frac{dR_{b1}}{dw_{b1}}$ are the reductions in marginal revenue from the marginal decrease in the proportion of fans from winning percentages. I summarize the results with the following proposition:

Proposition 7: If the revenue sharing adjusted increase in revenue from the strategic effect of winning percentage on the proportion of fans is greater the reduction in the revenue sharing adjusted marginal revenue of winning percentage from the marginal decrease in the proportion of fans from the winning percentage of the other team in the market then revenue sharing acts strategic substitutes. Otherwise, revenue sharing acts as strategic compliments.

Proof: See Appendix A

Section IV: An Example

$R_{ij} = \sigma_{ij} w_{ij}$ and the marginal revenue is positive and constant. Since market 1 is the large revenue potential market, $\sigma_{i1} > \sigma_{i2 \text{ or } 3}$. A contest success function (CSF) describes the production process and the interdependent relationship among the effort of participants and winning (Skaperdas, 1996). I impose the ratio form logistic function as the CSFs. First, I define, $w_{a1} = \frac{t_{a1}^{\phi_a}}{t_{a1}^{\phi_a} + t_{a2}^{\phi_a}}$, where ϕ_a is what Fort and Winfree (2009) call the talent parameter, which measures the degree to which talent affects winning percentages. I assume that the CSF is the same for both teams. Similarly, the proportion of total fans is defined as $\gamma_{a1} = \frac{w_{a1}^{\beta_{a1}}}{w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}}$, where β represents a sensitivity of fan preferences toward winning percentages. I also assume the following are true: $\frac{\partial \gamma_{a1}}{\partial w_{a1}} > 0$ and $\frac{\partial \gamma_{a1}}{\partial \beta_{a1}} > 0$, $\frac{\partial \gamma_{a1}}{\partial w_{b1}} < 0$, $\frac{\partial \gamma_{a1}}{\partial w_{b1}} < 0$. Since a and b represent different leagues I let the value of β vary across leagues.

Comparing the first order conditions of the cross-owned and duopolist firms, the cross-owned firm will invest less in talent by the amount of $\frac{\beta_{b1} w_{a1}^{\beta_{a1}} w_{b1}^{\beta_{b1}-1}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} \sigma_{b1} w_{b1}$, which is the reduction in marginal revenue due to the decrease in the proportion of fans. The greater the fans preferences are toward winning of the other team in the market, determined by β_{b1}, the greater the discrepancy in the talent levels between the firms.

Simplifying equation (7), the duopolist will invest a greater amount in talent compared to the monopolist if $\gamma(\beta_a,\beta_b)\beta_a > 1$. Therefore, in the duopoly case, the product of fan sensitivity toward winning and the probability of the proportion of fans must be greater than one for the duopolist to invest more in talent than the monopolist. In the case of the duoplist, $\gamma \in (0,1)$, therefore fans' preferences for winning must be greater. Larger values of β_b (fans' preference toward winning of the other team in the market) the smaller the value of γ. Therefore, larger values of β_a is required for $\gamma(\beta_a,\beta_b)\beta_a > 1$ to be true. Figure 3 graphs the required value of β_a for the condition where the duopolist will invest the same amount in talent than the monopolist ($\gamma(\beta_a,\beta_b)\beta_a = 1$) for the range of possible winning percentages of the team in league "a", holding constant at $\beta_b = 1,\ 1{,}5,\ \text{or } 2$, and the winning percentage of the team in league "b" at 500. The value of β_a decreases non-linearly with increases in β_b and increases w_{a1}.

The condition for the cross-owned firm to invest more in talent compared to the monopolist is $\gamma_{a1}\beta_{a1} > \frac{R_{a1}}{R_{a1} - R_{b1}}$ if $R_{a1} > R_{b1}$.[16] Therefore, the condition for the cross-owned firms to invest more in talent than the monopoly includes the effects of changes in talent levels on the relative revenue of both its teams. If $R_{b1} = 0$, the condition simplifies

[16] The conditions are the same if $R_{a1} < R_{b1}$ but the numbers are negative.

to the case of duopolist. If $R_{a1} > R_{b1}$, then the condition for the cross-owned firm to invest more in talent is more difficult to satisfy than the condition for the duopolist.

The equations that calculate the strategic effects have $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1} \partial w_{b1}} R_{a1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}} \frac{dR_{a1}}{dw_{a1}}$ embedded within them. Written with functional form is

$\frac{\beta_{a1}\beta_{b1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}-1} (w_{a1}^{\beta_{a1}} - w_{b1}^{\beta_{b1}})}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^3} \sigma_{a1} w_{a1} + \frac{-\beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} \sigma_{a1}$. The condition is positive if $(\gamma_{a1} - \gamma_{b1})\beta_{a1} > 1$ if $w_{a1}^{\beta_{a1}} > w_{b1}^{\beta_{b1}}$. Again, β_{a1} must be greater than one for this to be satisfied.

Section V: Conclusions

This paper has shown that if sports fans make consumption choices based on the quality of all of the teams located in their markets that indirect competition and the ownership structure alters an owner's incentive to invest in talent. In addition, league policies can have an effect on the quality of teams in other leagues. This has important implications for policy makers. One reason that sports leagues are permitted to operate with monopoly power is to preserve the product produced. However, cross-ownership is a relationship between leagues. Therefore, cross-ownership is not intended to preserve the product. In contrast, it is shown that cross-ownership reduces the quality of teams. Beyond the normative issues and the utility fans gain from winning, incentive to invest in talent has direct effects on completive balance and players' salaries.

All analysis pertaining to league policies is important because they are at the center of work-stoppages. The analysis of cross-league effects on league policies is important because leagues are operated from a cartel of owners. As shown in this paper, owners belonging to multiple cartels have different incentives than owners not belonging to multiple cartels. This paper is a first attempt at understanding these incentives.

Extensions to this work are plenty. Empirical work is obvious. The effect of cross-ownership on league expansion and relocation is important. The model in this paper can be extended to analyze the effects of indirect competition and ownership structure on competitive balance and players' salaries. Further study into the pricing effects and efficiency gains caused by cross-ownership is worthwhile. Models that examine the effects of ownership structures in professional sports, beyond cross-ownership, would be welcome additions to the literature.

The study of indirect substitutes might be more important in sports than other industries because territorial rights have eliminated almost all direct competition. This provides yet another unique opportunity for economists and sports researchers to explore, test, and make useful recommendations. My analysis provides a theoretical framework for future sports economics research to build upon.

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TABLES AND FIGURES

Figure 1. The number of markets with at least 1 team from each league (MLB, NBA, and the NHL) and number of cross-owned firms.

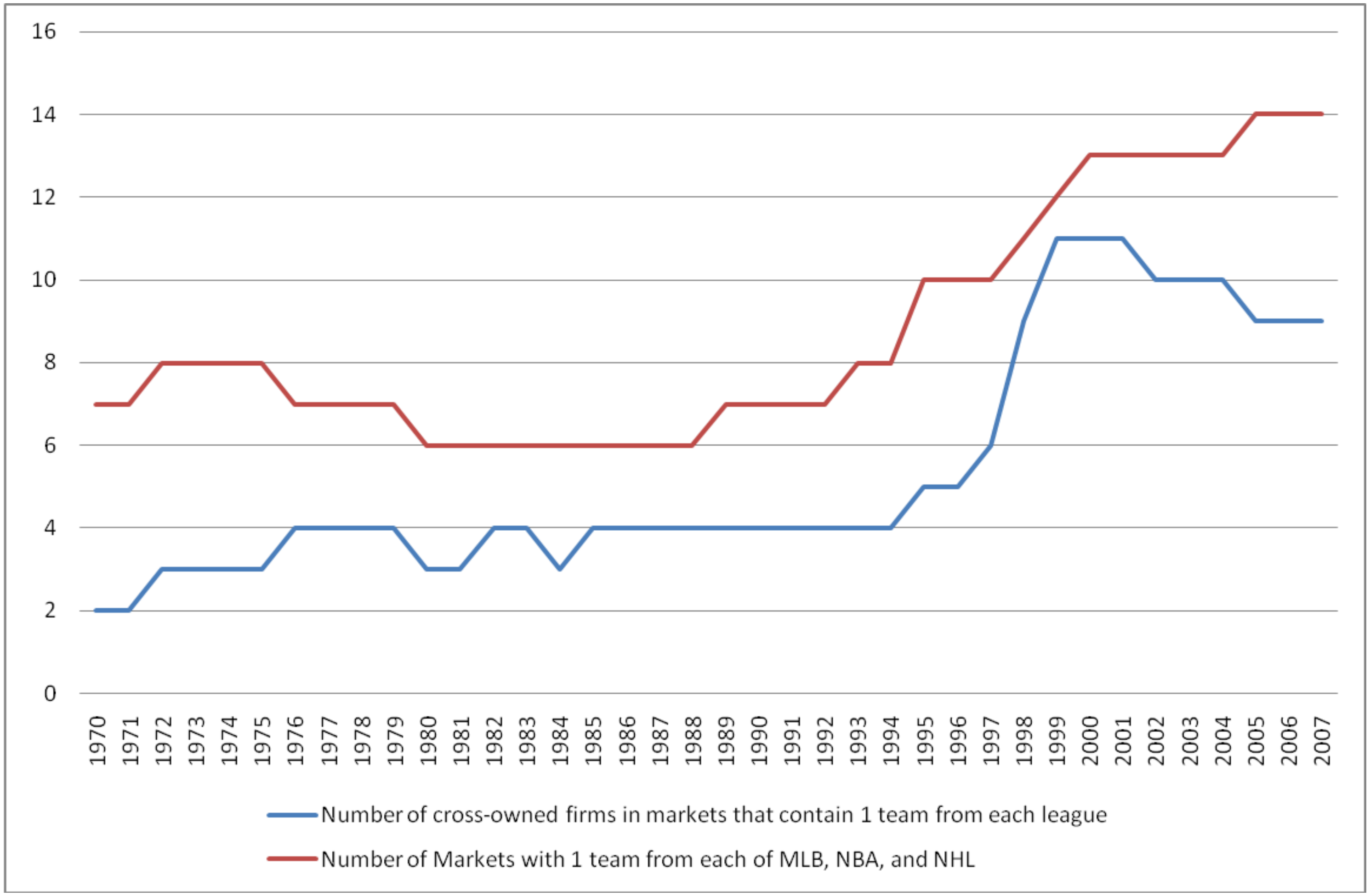


Table 2. Cross-Ownership between teams in the NBA, MLB, and NHL

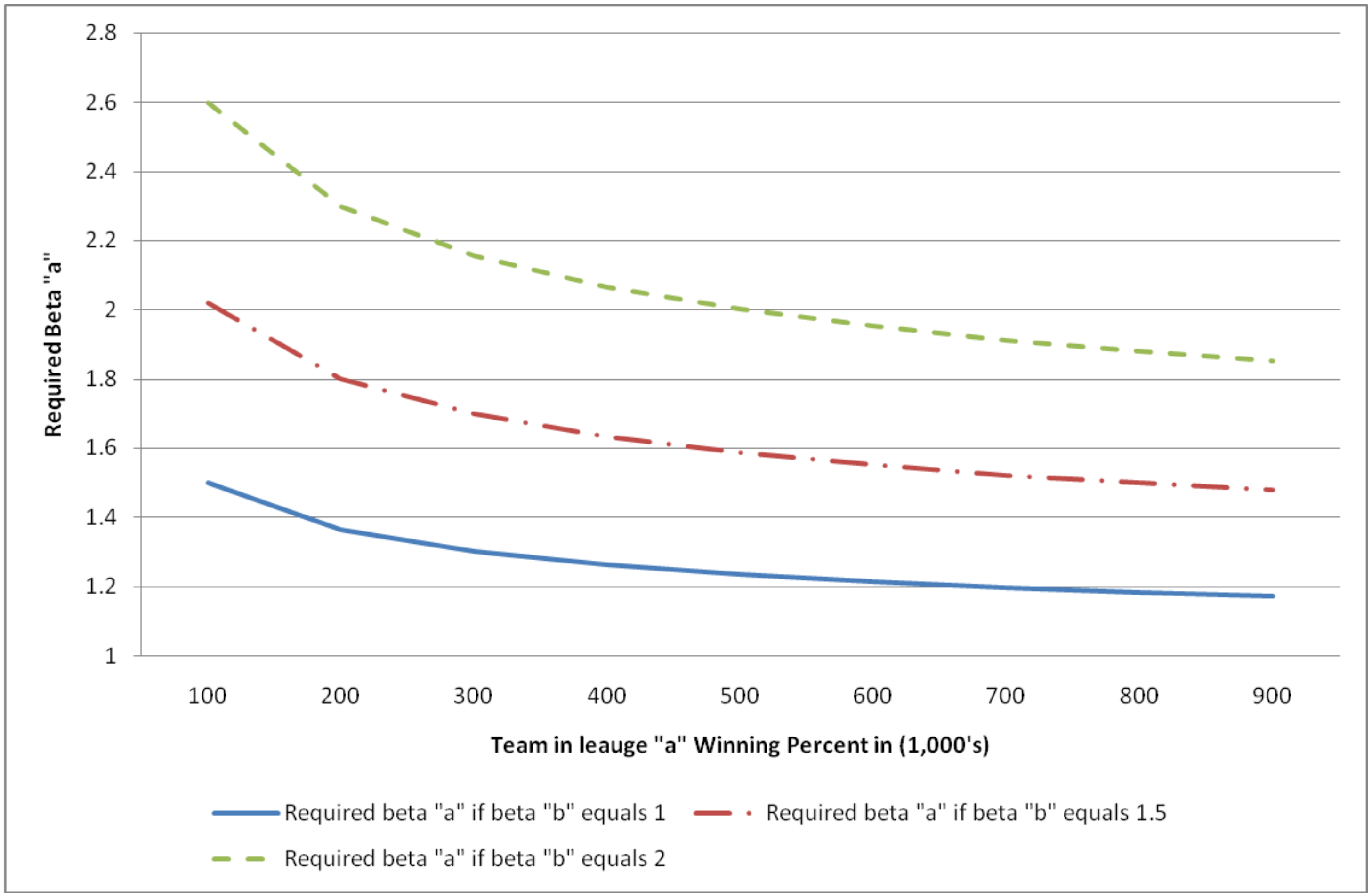
Location	Years	NBA Team	MLB Team	NHL Team
Phoenix	1998 – 2004	Phoenix Suns	Arizona Diamondbacks	
Atlanta	1976-2004	Atlanta Hawks	Atlanta Braves	
	1999-2003	Atlanta Hawks	Atlanta Braves	Atlanta Thrashers
	2003-present	Atlanta Hawks		Atlanta Thrashers
Washington[17]	1975-1999	Washington Wizards		Washington Capitals
	1999-2006	Washington Wizards		Washington Capitals
Boston	1951-1963	Boson Celtics		Boston Bruins
Chicago	1985-present	Chicago Bulls	Chicago White Sox	
Dallas	1998-present		Texas Rangers	Dallas Stars
Denver	1995-1998	Denver Nuggets		Colorado Avalanche
	1998-2000	Denver Nuggets		Colorado Avalanche
	2000-present	Denver Nuggets		Colorado Avalanche
Detroit	1982-present		Detroit Tigers	Detroit Red Wings
Detroit/Tampa Bay		Detroit Pistons		Tampa Bay Lightning
Los Angeles	1967-1979	Los Angeles Lakers		Los Angeles Kings
	1979-1988	Los Angeles Lakers		Los Angeles Kings
	1999-present	Los Angeles Lakers		Los Angeles Kings
	1997-2005		Los Angeles Angels of Anaheim	Anaheim Ducks
Miami	1993-1998		Florida Marlins	Florida Panthers
New York	1946-present	New York Knicks		New York Rangers
	2000- 2004	New Jersey Nets	New York Yankees	New Jersey Devils
Philadelphia	1997-present	Philadelphia 76ers		Philadelphia Flyers
Toronto	1996-present	Toronto Raptors		Toronto Maple Leafs
Vancouver	1995-2001	Vancouver Grizzles		Vancouver Canucks

[17] Abe Pollin currently remains part owner of the NHL's Washington Capitals.

Table 3: Summary of cross-ownership firm among cities with a team from each league (MLB, NBA, and the NHL)

Markets	Cross-Ownership Group	Leagues
New York	Madison Square Garden Corp. & Yankee Global Enterprises LLC	NBA/NHL & NBA/NHL/MLB
Los Angeles	AEG Company and others	NBA/NHL
Chicago	Jerry Reinsdorf and other	MLB, NBA
Toronto	Maple Leafs Sports and Entertainment	NHL, NBA
Detroit	Olympia Entertainment	NHL, MLB
Dallas	Thomas Hicks	NHL, MLB
Denver	Kroenke Sports Enterprise	NHL, NBA
Philadelphia	Comcast Corp.	NHL, NBA
Boston	Boston Garden Co.	NHL, NBA
Atlanta	Time Warner/Atlanta Spirit LLC.	NHL, NBA, MLB
Miami	Wayne Huizenga	NHL, NBA
Washington	Abe Pollin	NHL, NBA
Phoenix	Jerry Colangelo	NBA, MLB
Minneapolis	NA	NA

Figure 3: The values of β_a that make $\gamma(\beta_a, \beta_b)\beta_a = 1$ (the condition where the dupolist will invest the same amount in talent as the monopolist) for different winning percents of the team in league "a" holding the value of β_b constant at 1, 1.5, and 2 and the winning percent of team "b" at 500.



Appendix A: Derivations of Theoretical Equations

The condition for the duopolist to invest more in talent than the monopolist given by equation (7) is derived by setting (5) greater than (3) as follows:

$$\frac{\partial \gamma_{a1}}{\partial w_{a1}}\frac{\partial w_{a1}}{\partial t_{a1}}R_{a1}+\gamma_{a1}\frac{dR_{a1}}{dw_{a1}}\frac{\partial w_{a1}}{\partial t_{a1}}-1>\frac{dR_{a1}}{dw_{a1}}\frac{\partial w_{a1}}{\partial t_{a1}}-1$$
$$\rightarrow \frac{\partial \gamma_{a1}}{\partial w_{a1}}\frac{\partial w_{a1}}{\partial t_{a1}}R_{a1}>\frac{dR_{a1}}{dw_{a1}}\frac{\partial w_{a1}}{\partial t_{a1}}-\gamma_{a1}\frac{dR_{a1}}{dw_{a1}}\frac{\partial w_{a1}}{\partial t_{a1}}$$
$$\rightarrow \frac{\partial \gamma_{a1}}{\partial w_{a1}}R_{a1}>\frac{dR_{a1}}{dw_{a1}}-\gamma_{a1}\frac{dR_{a1}}{dw_{a1}}$$
$$\rightarrow \frac{\partial \gamma_{a1}}{\partial w_{a1}}R_{a1}>\left(1-\gamma_{a1}\right)\frac{dR_{a1}}{dw_{a1}}$$
$$\rightarrow \frac{\partial \gamma_{a1}}{\partial w_{a1}}R_{a1}\frac{w_{a1}}{\gamma_{a1}}>\left(1-\gamma_{a1}\right)\frac{dR_{a1}}{dw_{a1}}\frac{w_{a1}}{\gamma_{a1}}$$
$$\rightarrow \frac{\partial \gamma_{a1}}{\partial w_{a1}}\frac{w_{a1}}{\gamma_{a1}}>\left(1-\gamma_{a1}\right)\frac{dR_{a1}}{dw_{a1}}\frac{w_{a1}}{R_{a1}}\frac{1}{\gamma_{a1}}$$
$$\rightarrow \gamma_{a1}R_{a1}\varepsilon_{\gamma,w}>\left(1-\gamma_{a1}\right)R_{a1}\varepsilon_{r,w}$$

The strategic effect on talent is given by equation (8)

$$\frac{\partial^2 \pi_{a1}}{\partial t_{a1}\partial t_{b1}}=\frac{\partial w_{a1}}{\partial t_{a1}}\frac{\partial w_{b1}}{\partial t_{b1}}\left(\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}R_{a1}+\frac{\partial \gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}}\right)$$

The functions $\frac{\partial w_{a1}}{\partial t_{a1}}$ and $\frac{\partial w_{b1}}{\partial t_{b1}}$ are both positive. Therefore the sign of (8) is determined by the sign of the terms in the brackets. The sign of each of the four respective terms in the brackets are: $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}R_{a1}+\frac{\partial \gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}}$ (ambiguous)(positive)+(negative)(positive). Therefore, talent acts as strategic compliments if $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}R_{a1}>-\frac{\partial \gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}}$ and strategic substitutes otherwise. Similarly the condition for the cross-owned firm to invest more in talent than the monopolist given by equation (12) is derived by setting (11) greater than (3) as follows:

$$\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1} > (1-\gamma_{a1}) \frac{dR_{a1}}{dw_{a1}}$$

$$\frac{\partial \gamma_{a1}}{\partial w_{a1}} \frac{\partial w_{a1}}{\partial t_{a1}} R_{a1} + \gamma_{a1} \frac{dR_{a1}}{dw_{a1}} \frac{\partial w_{a1}}{\partial t_{a1}} + \frac{\partial \gamma_{b1}}{\partial w_{a1}} \frac{\partial w_{a1}}{\partial t_{a1}} R_{b1} > \frac{dR_{a1}}{dw_{a1}} \frac{\partial w_{a1}}{\partial t_{a1}}$$

$$\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1} > \frac{dR_{a1}}{dw_{a1}} - \gamma_{a1} \frac{dR_{a1}}{dw_{a1}}$$

$$\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1} > \left(1-\gamma_{a1}\right) \frac{dR_{a1}}{dw_{a1}}$$

$$\gamma_{a1} \varepsilon_{\gamma_{a1}, w_{a1}} + \gamma_{a1} \frac{\partial \gamma_{b1}}{\partial w_{a1}} \frac{w_{a1}}{\gamma_{a1}} \frac{R_{b1}}{R_{a1}} > \left(1-\gamma_{a1}\right) \varepsilon_{R_{a1}, w_{a1}}$$

$$\gamma_{a1} R_{a1} \varepsilon_{\gamma_{a1}, w_{a1}} + \gamma_{b1} R_{b1} \varepsilon_{\gamma_{b1}, w_{a1}} > \left(1-\gamma_{a1}\right) R_{a1} \varepsilon_{R_{a1}, w_{a1}}$$

The strategic equation in equation (8) is derived as follows:

$$\frac{\partial^2 \pi_{a1}}{\partial t_{a1} \partial t_{b1}} = \frac{\partial w_{a1}}{\partial t_{a1}} \frac{\partial w_{b1}}{\partial t_{b1}} \left(\frac{\partial^2 \gamma_{a1}}{\partial w_{a1} \partial w_{b1}} R_{a1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}} \frac{dR_{a1}}{dw_{a1}} \right)$$

$$\rightarrow \frac{\partial}{\partial t_{b1}} \left(\frac{\partial \pi_{a1}}{\partial t_{a1}} \right) = \frac{\partial}{\partial t_{b1}} \left(\frac{\partial \gamma_{a1}}{\partial w_{a1}} \frac{\partial w_{a1}}{\partial t_{a1}} R_{a1} + \gamma_{a1} \frac{dR_{a1}}{dw_{a1}} \frac{\partial w_{a1}}{\partial t_{a1}} - 1 \right)$$

$$\rightarrow \frac{\partial^2 \gamma_{a1}}{\partial w_{a1} \partial w_{b1}} \frac{\partial w_{b1}}{\partial t_{b1}} \frac{\partial w_{a1}}{\partial t_{a1}} R_{a1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}} \frac{\partial w_{b1}}{\partial t_{b1}} \frac{dR_{a1}}{dw_{a1}} \frac{\partial w_{a1}}{\partial t_{a1}}$$

$$\rightarrow \frac{\partial w_{a1}}{\partial t_{a1}} \frac{\partial w_{b1}}{\partial t_{b1}} \left(\frac{\partial^2 \gamma_{a1}}{\partial w_{a1} \partial w_{b1}} R_{a1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}} \frac{dR_{a1}}{dw_{a1}} \right)$$

The derivations of the other of the strategic effects are similar.

The equations for the effects of revenue sharing on other leagues are derived by setting the two first order conditions equal to each other and using the two-team league model equilibrium condition of $\frac{\partial w_{b1}}{\partial t_{b1}} = -\frac{\partial w_{b2}}{\partial t_{b1}}$. This results in the following series of equations resulting in equation (20).

$$\alpha \frac{\partial w_{b1}}{\partial t_{b1}}\left(\frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1}+\gamma_{b1} \frac{dR_{b1}}{dw_{b1}}\right)+(1-\alpha)\frac{dR_{b2}}{dw_{b2}}\left(-\frac{\partial w_{b1}}{\partial t_{b1}}\right)=(1-\alpha)\frac{\partial w_{b1}}{\partial t_{b2}}\left(\frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1}+\gamma_{b1} \frac{dR_{b1}}{dw_{b1}}\right)+\alpha \frac{dR_{b2}}{dw_{b2}} \frac{\partial w_{b2}}{\partial t_{b2}}$$

$$\rightarrow \alpha \frac{\partial w_{b1}}{\partial t_{b1}}\left(\frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1}+\gamma_{b1} \frac{dR_{b1}}{dw_{b1}}\right)+(1-\alpha)\frac{\partial w_{b1}}{\partial t_{b2}}\left(\frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1}+\gamma_{b1} \frac{dR_{b1}}{dw_{b1}}\right)=\frac{dR_{b2}}{dw_{b2}}\left(\alpha \frac{\partial w_{b2}}{\partial t_{b2}}+(1-\alpha)\frac{\partial w_{b1}}{\partial t_{b1}}\right)$$

$$\rightarrow\left(\gamma_{b1} \frac{dR_{b1}}{dw_{b1}}+\frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1}\right)\left(\alpha \frac{\partial w_{b1}}{\partial t_{b1}}+(1-\alpha)\frac{\partial w_{b1}}{\partial t_{b2}}\right)=\frac{dR_{b2}}{dw_{b2}}\left(\alpha \frac{\partial w_{b2}}{\partial t_{b2}}+(1-\alpha)\frac{\partial w_{b1}}{\partial t_{b1}}\right)$$

and $\frac{dTR_{b1}}{dw_{b1}}=\frac{\partial \gamma_{b1}}{\partial w_{b1}} R_{b1}+\gamma_{b1} \frac{dR_{b1}}{dw_{b1}}$ then,

$$\frac{dTR_{b1}}{dw_{b1}}\left(\alpha \frac{\partial w_{b1}}{\partial t_{b1}}+(1-\alpha)\frac{\partial w_{b2}}{\partial t_{b2}}\right)=\frac{dR_{b2}}{dw_{b2}}\left(\alpha \frac{\partial w_{b2}}{\partial t_{b2}}+(1-\alpha)\frac{\partial w_{b1}}{\partial t_{b1}}\right)$$

The equation for the effects of revenue sharing on cross-ownership is determined by differentiating the first order condition, $\frac{\partial^2 \pi_{a1,b1}}{\partial t_{a1}\partial \alpha}$, to obtain equation (23) in the following way.

$$\frac{\partial \pi_{a1,b1}}{\partial t_{a1}\partial \alpha} = \frac{\partial}{\partial \alpha}\left[\frac{\partial w_{a1}}{\partial t_{a1}}\left(\begin{array}{l} \frac{\partial \gamma_{a1}\left(w_{a1}, w_{b1}(t_{b1}(\alpha), t_{b2}(\alpha))\right)}{\partial w_{a1}} R_{a1} \\ +\gamma_{a1}\left(w_{a1}, w_{b1}(t_{b1}(\alpha), t_{b2}(\alpha))\right)\frac{dR_{a1}}{dw_{a1}} \\ +\alpha \frac{\partial \gamma_{b1}\left(w_{b1}(t_{b1}(\alpha), t_{b2}(\alpha)), w_{a1}\right)}{\partial w_{a1}} R_{b1}(w_{b1}\left(t_{b1}(\alpha), t_{b2}(\alpha)\right) \end{array}\right)\right]$$

and $\frac{\partial}{\partial \alpha}\left(\frac{\partial \gamma_{a1}\left(w_{a1}, w_{b1}(t_{b1}(\alpha), t_{b2}(\alpha))\right)}{\partial w_{a1}} R_{a1}\right)$

$$= \left(\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right)R_{a1}\right),$$

and $\frac{\partial}{\partial \alpha}\left(\gamma_{a1}\left(w_{a1}, w_{b1}(t_{b1}(\alpha), t_{b2}(\alpha))\right)\frac{dR_{a1}}{dw_{a1}}\right)$

$$= \frac{\partial \gamma_{a1}}{\partial w_{b1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right)\frac{dR_{a1}}{dw_{a1}},$$

and $\frac{\partial}{\partial \alpha}\left(\alpha \frac{\partial \gamma_{b1}\left(w_{b1}(t_{b1}(\alpha), t_{b2}(\alpha)), w_{a1}\right)}{\partial w_{a1}} R_{b1}(w_{b1}\left(t_{b1}(\alpha), t_{b2}(\alpha)\right)\right)$

$$= \alpha\left(\frac{\partial \gamma_{b1}}{\partial w_{a1}}\frac{dR_{b1}}{dw_{b1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right) + R_{b1}\frac{\partial^2 \gamma_{b1}}{\partial w_{a1}\partial w_{b1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right)\right)$$

therefore, $$\frac{\partial^2 \pi_{a1,b1}}{\partial t_{a1}\partial \alpha} = \frac{\partial w_{a1}}{\partial t_{a1}}\left(\begin{array}{l} \left(\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right)R_{a1}\right) \\ +\frac{\partial \gamma_{a1}}{\partial w_{b1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right)\frac{dR_{a1}}{dw_{a1}} \\ +\alpha\left(\begin{array}{l} \frac{\partial \gamma_{b1}}{\partial w_{a1}}\frac{dR_{b1}}{dw_{b1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right) \\ +R_{b1}\frac{\partial^2 \gamma_{b1}}{\partial w_{a1}\partial w_{b1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right) \end{array}\right) \end{array}\right)$$

$$\rightarrow \frac{\partial w_{a1}}{\partial t_{a1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right)\left[\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}R_{a1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}} + \alpha\left(\frac{\partial \gamma_{b1}}{\partial w_{a1}}\frac{dR_{b1}}{dw_{b1}} + \frac{\partial^2 \gamma_{b1}}{\partial w_{a1}\partial w_{b1}}R_{b1}\right)\right]$$

$$\rightarrow \frac{\partial w_{a1}}{\partial t_{a1}}\left(\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha} + \frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}\right)\left[\frac{\partial^2 \gamma_{a1}}{\partial w_{a1}\partial w_{b1}}R_{a1} + \alpha\frac{\partial^2 \gamma_{b1}}{\partial w_{a1}\partial w_{b1}}R_{b1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}} + \alpha\frac{\partial \gamma_{b1}}{\partial w_{a1}}\frac{dR_{b1}}{dw_{b1}}\right]$$

The condition for proposition 7 is as follows. If $\frac{\partial w_{b1}}{\partial t_{b1}}\frac{dt_{b1}}{d\alpha}+\frac{\partial w_{b1}}{\partial t_{b2}}\frac{dt_{b2}}{d\alpha}<0$ the equation (23) is positive (negative) if the term in the square brackets is negative (positive). Therefore revenue sharing acts as strategic compliments if $\frac{\partial^2\gamma_{a1}}{\partial w_{a1}\partial w_{b1}}R_{a1}+\alpha\frac{\partial^2\gamma_{b1}}{\partial w_{a1}\partial w_{b1}}R_{b1}<-\left(\frac{\partial\gamma_{a1}}{\partial w_{b1}}\frac{dR_{a1}}{dw_{a1}}+\alpha\frac{\partial\gamma_{b1}}{\partial w_{a1}}\frac{dR_{b1}}{dw_{b1}}\right)$ and strategic substitutes otherwise.

Appendix B: Derivation of Examples

The most common form of the CSF, $w_{a1} = \frac{t_{a1}^{\phi_a}}{t_{a1}^{\phi_a} + t_{a2}^{\phi_a}}$. Its derivative does not need to be derived because it is divided out of each derivation.

Using a similar logistic form to determine the proportion of demanders $\gamma_{a1} = \frac{w_{a1}^{\beta_{a1}}}{w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}}$ assuming $\frac{dw_{b1}^{\beta_{b1}}}{dw_{a1}^{\beta_{a1}}} = 0$ and only that $\beta_{a1} > 0$, then the derivatives of interest are as follows:

$$\frac{\partial \gamma_{a1}}{\partial w_{a1}} = \frac{\beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}}}{\left(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}\right)^2} > 0$$

$$\frac{\partial \gamma_{a1}}{\partial w_{b1}} = \frac{-\beta_{b1} w_{a1}^{\beta_{a1}} w_{b1}^{\beta_{b1}-1}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} < 0$$

$$\frac{\partial^2 \gamma_{a1}}{\partial w_{a1} \partial w_{b1}} = \frac{\beta_{a1} \beta_{b1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}-1} (w_{a1}^{\beta_{a1}} - w_{b1}^{\beta_{b1}})}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^3}$$

$$\frac{\partial^2 \gamma_{a1}}{\partial w_{a1} \partial w_{b1}} = -\frac{\partial^2 \gamma_{b1}}{\partial w_{a1} \partial w_{b1}}$$

Therefore, to determine the amount that the duopolist will invest in talent than the cross-owned firm is determined by comparing their first-order conditions (equations (5) and (11)) as follows:

Duopolist>Cross-Owned Firm

$$\frac{\partial w_{a1}}{\partial t_{a1}} \left(\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \gamma_{a1} \frac{dR_{a1}}{dw_{a1}} \right) > \frac{\partial w_{a1}}{\partial t_{a1}} \left(\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \gamma_{a1} \frac{dR_{a1}}{dw_{a1}} + \frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1} \right)$$

$$\to 0 > \frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1}$$

$$\to 0 > \frac{-\beta_{b1} w_{a1}^{\beta_{a1}} w_{b1}^{\beta_{b1}-1}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} \sigma_{b1} w_{b1}$$

Condition where the duopolist will invest more in talent compared to the monopolist: Equation 7

$$\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} > (1-\gamma_{a1}) \frac{dR_{a1}}{dw_{a1}} (7)$$

$$\rightarrow \frac{\beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} \sigma_{a1} w_{a1} > \left(1 - \frac{w_{a1}^{\beta_{a1}}}{w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}}\right) \sigma_{a1}$$

$$\rightarrow \frac{\beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} w_{a1} > 1 - \frac{w_{a1}^{\beta_{a1}}}{w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}}$$

$$\rightarrow \frac{\beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} w_{a1} > \frac{w_{1}^{\beta_{b1}}}{w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}}$$

$$\rightarrow \beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}} w_{a1} > w_{b1}^{\beta_{b1}} \left(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}} \right)$$

$$\rightarrow \beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}} w_{a1} > w_{a1}^{\beta_{a1}} w_{b1}^{\beta_{b1}} + w_{b1}^{\beta_{b1}} w_{b1}^{\beta_{b1}}$$

$$\rightarrow \beta_{a1} > \frac{w_{a1}^{\beta_{a1}} w_{b1}^{\beta_{b1}} + w_{b1}^{\beta_{b1}} w_{b1}^{\beta_{b1}}}{w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}} w_{a1}}$$

$$\rightarrow \beta_{a1} > \frac{w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}}{w_{a1}^{\beta_{a1}}}$$

$$\rightarrow \beta_{a1} > \frac{1}{\gamma_{a1}}$$

$$\rightarrow \gamma_{a1} \beta_{a1} > 1$$

Condition where the cross-owned firm will invest more in talent compared to the monopolist: Equation 12

$$\frac{\partial \gamma_{a1}}{\partial w_{a1}} R_{a1} + \frac{\partial \gamma_{b1}}{\partial w_{a1}} R_{b1} > (1-\gamma_{a1}) \frac{dR_{a1}}{dw_{a1}}$$

with the logistic specification: $\frac{\partial \gamma_{a1}}{\partial w_{a1}} = -\frac{\partial \gamma_{b1}}{\partial w_{a1}}$

$$\rightarrow \frac{\partial \gamma_{a1}}{\partial w_{a1}} (R_{a1} - R_{b1}) > (1-\gamma_{a1}) \frac{dR_{a1}}{dw_{a1}}$$

$$\rightarrow \frac{\beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} (R_{a1} - R_{b1}) > \left(1 - \frac{w_{a1}^{\beta_{a1}}}{w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}}\right) \sigma_{a1}$$

$$\rightarrow \frac{\beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} (R_{a1} - R_{b1}) > \frac{w_{b1}^{\beta_{b1}}}{w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}} \sigma_{a1}$$

$$\rightarrow \beta_{a1}(R_{a1} - R_{b1}) > \frac{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}) w_{a1} \sigma_{a1}}{w_{a1}^{\beta_{a1}}}$$

$$\rightarrow \beta_{a1}(R_{a1} - R_{b1}) > \frac{1}{\gamma_{a1}} R_{a1}$$

$$\rightarrow \beta_{a1}(R_{a1} - R_{b1}) > R_{a1}$$

$$\rightarrow \gamma_{a1}\beta_{a1} > \frac{R_{a1}}{(R_{a1} - R_{b1})} \text{ if } R_{a1} > R_{b1}, \text{ or}$$

$$\rightarrow \gamma_{a1}\beta_{a1} < \frac{R_{a1}}{(R_{a1} - R_{b1})} \text{ if } R_{a1} < R_{b1},$$

The simplification of strategic effects is as follows. All of the strategic effects have $\frac{\partial^2 \gamma_{a1}}{\partial w_{a1} \partial w_{b1}} R_{a1} + \frac{\partial \gamma_{a1}}{\partial w_{b1}} \frac{dR_{a1}}{dw_{a1}}$ embedded within them. Using the functional forms, this equation is positive if $\frac{\beta_{a1}\beta_{b1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}-1} (w_{a1}^{\beta_{a1}} - w_{b1}^{\beta_{b1}})}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^3} \sigma_{a1} w_{a1} + \frac{-\beta_{a1} w_{a1}^{\beta_{a1}-1} w_{b1}^{\beta_{b1}}}{(w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}})^2} \sigma_{a1} > 0$, which simplifies to $\beta_{a1} > \frac{w_{a1}^{\beta_{a1}} + w_{b1}^{\beta_{b1}}}{w_{a1}^{\beta_{a1}} - w_{b1}^{\beta_{b1}}}$ and then $(\gamma_{a1} - \gamma_{b1})\beta_{a1} > 1$, if $w_{a1}^{\beta_{a1}} > w_{b1}^{\beta_{b1}}$.

Appendix C: Details of the progression of cross-ownership

As of 1970, five markets had a team from each of the three leagues: New York, Los Angeles, San Francisco, Boston, and Chicago. Of these five markets, three of them included cross-ownership structures: New York, Los Angeles, and Boston – and San Francisco only had teams from different leagues until 1973. Madison Square Garden Corporation has owned both the New York Rangers of the NHL and the New York Knicks of the NBA since 1946. Jack Kent Cooke first owned both the NHL's Los Angeles Kings and the NBA's Los Angeles Lakers in 1967 and they remain part of the same ownership group today, even though they have been sold four times. In Boston, Walter Brown owned both an NHL team and NBA team for 12 years between 1951 and 1963. In 1972 Chicago's Arthur Wirtz owned both an NBA and NHL team until he died in 1983. Jerry Reinsdorf continued the cross-ownership trend in Chicago by simultaneously owning both a MLB and NBA team from 1985 through to the present.

At the time of the NHL first attempt in Atlanta, 1972, the market already consisted of MLB's Braves and the NBA's Hawks. In 1976, Ted Turner purchased the Braves and the Hawks. Atlanta relocated to Calgary in 1979. The city of Atlanta ended up becoming a three-team city again when the NHL expanded back to Atlanta in the form of the Thrashers in 1999. However, the Thrashers were part of Time Warner that owned each team from all three leagues[18]. The NHL and NBA were sharing the market in Washington for only three years before Capital's owner Abe Pollin purchased the Wizards to run the Capitals and Wizards as a single firm. Pollin continued to own both teams until 1999 when he divested the NHL's Capitals to owner Ted Leonis. Pollin

[18] In 2003 Time Warner divested of its professional sports teams. The Thrashers and Hawks became owned by the Atlanta Spirit and the Braves by Liberty Media Group.

remains as a minority shareholder. In 1995, Tom Hicks purchased the Dallas Stars and three years later purchased the Texas Rangers. Currently, Hicks owns both the Stars and Rangers. Similar to Atlanta, after a failed attempt, the NHL was able to be successful in Denver as part of a cross-owned firm, Comcast Corporation, which owns both an NBA and NHL team. Mike Illich has owned both the NHL's Red Wings and MLB's Tigers franchises in Detroit since 1982 and because the NBA's Pistons play their games out of the city center where both the Red Wings and Tigers play, his firm owns the entire professional sports market in downtown Detroit. The NBA was the first to move into the Miami market, expanding to include the Miami Heat in 1998. Major League Baseball and the NHL entered the Miami market in 1999 together under owner Wayne Huizenga. Philadelphia was represented with individual ownership of each of the three professional leagues prior to 1970. In 1997, Comcast-Spectator that owned the NHL's Flyers' purchased the NBA's 76'ers. In 1998, MLB awarded the NBA's Phoenix Suns owner, Jerry Colangelo, an expansion team. Toronto Maple Leafs formed Maple Leafs Sports and Entertainment and purchased the Toronto Raptors after they joined the city in 1998, three years after their expansion into the city.

CHAPTER 3: A COMPARISON OF TELEVISION AND GATE DEMAND IN THE NATIONAL BASKETBALL ASSOCIATION

Abstract

I estimate the demand for gate attendance and television audiences in the NBA and find that the fans who attend games live are inherently different from fans who watch games on television. Fans who watch the games on television are more sensitive to winning, and do not substitute for other professional sports leagues, compared to fans who attend the games. The effects of winning on demand for television compared to gate attendance can have consequences for competitive balance.

INTRODUCTION

Although media is an important and growing revenue source for sports teams, little is known about the factors of demand for games on television. For the 2007-08 season, the National Basketball Association (NBA) received $4.6 billion from league-wide contracts from ABC/ESPN and AOL/Time Warner, and this does not include local television rights. Media revenue typically accounts for over one-third of total revenue for teams in the NBA, and it is sometimes greater than stadium revenue. However, a vast majority of the literature that estimates demand for sports teams, estimates attendance. This is somewhat understandable since attendance data is typically easier to obtain. Nonetheless, given the growing importance of media revenue, more needs to be known about fans who watch games on television. The goal of this study is to estimate television demand for the NBA and compare and contrast this with demand for attendance.

I analyzed annual local media television ratings to see how fans who watch NBA games on television are inherently different from fans who watch the games in person. It has been well documented that factors such as team quality, income, population, and substitutes will affect sports attendance, but little is known about these effects on television audiences for sports teams. It may be the case that fans who watch the NBA on television are generally a different group from fans who typically go to the game. It may also be the case that certain variables cause a substitution between television and attendance. Regardless, teams and researchers should have some understanding of the different types of demand. For example, it may be the case that NBA attendance is a normal good, but the NBA television audiences are an inferior good. Therefore, the effect of incomes on a team's revenue may be ambiguous, which may affect the feasibility of potential markets.

Much of the literature on the demand for sports television has focused on the substitution between watching a game on television and watching a game live for European football fans (Baimbridge et al. (1996), Allan (2004), Forrest et al. (2004), Buraimo et al. (2006), Buraimo (2008), Allen and Roy (2008)), Rugby fans (Baimbridge et al. (1995), Carmichael et al. (1999)), college football fans (Kaempfer and Pacey (1986), Fizel and Bennett (1989)) and National Football League fans (Siegfried and Hinshaw (1979), Zuber and Gandar (1988), Putsis and Sen (2000)). Other factors for television, such as uncertainty of outcome (Forrest et al., 2005), have been found to be significant factors affecting the demand for television audiences.

Much of the analysis of the NBA is focused on salary discrimination (Becker (1971), Kahn (1991) Wallace (1998), Jenkins (1996), Hamilton (1997), Kanazawa (2001), Bodvarsson (1999 and 2001)), and productivity (Kock (1988), McCormick (2001), Berri (2006)), while some analysis is concentrated on the demand for particular players and their externalities (Hausman and Leonard (1997), Berri (2004)). Another line of research draws attention to the impact and motivation of rule changes in the NBA. Taylor (2002) examines how the introduction of the NBA draft lottery reduced the incentive of teams that were eliminated from the playoffs to lose games, and Caudill (1998) argues that the NBA changed its playoff format to increase revenue rather than to reduce travel time for teams. Some studies have focused on gate demand. Leadly and Zygmont (2005) examine new-facility effects on demand in a number of professional sports including the NBA. Centering on race, Burdekin and Hossfeld (2005) and Burdekin and Idson (1991) estimate gate demand. They find that customer preferences toward race influence gate revenues. Similarly, using Nielsen ratings for local television NBA games, Kanazawa and Funk (2005) find that television viewership increases when there is a greater participation by players who are white.

Besides being a critical part of the team's revenue stream, the sensitivity of television fans to winning can also alter an owner's incentive to invest in winning. Therefore win percent is a key variable to understand. Television fans' preferences to winning alone can either improve or reduce competitive balance in leagues.

Data and Empirical Estimation

In this article, demands for attendance and television are estimated for 6 years from the 1999-00 to the 2004-05 seasons. Nielsen local cable ratings are used to derive television attendance for US based teams. Nielsen ratings are a statistical estimate of the percentage of people watching a particular television program within the designated marketing area (DMA).

Since the Nielsen ratings data represents the average viewership in the area per game, I construct a metric that approximates per capita season television audience. Using this data I derive the size of the per capita annual television audience as:

$$Per\ Capita\ TV\ Attendance = Neilson\ Ratings \times Number\ of\ Games \quad (1)$$

Given the nature of the professional sports television market in the United States, I make the assumption that all games are televised on local cable networks, setting the number of games televised to 82 for all teams.

Between the 1999-00 and 2004-05 seasons there were two team relocations: the Charlotte Hornets relocated to New Orleans, and the Vancouver Grizzlies relocated to Memphis for the start of the 2002-03 season. Nielsen ratings were unavailable for nine years dispersed throughout that data and were therefore not included. Also, Nielsen reported ratings for two different television stations in the case of Atlanta and Chicago for 5 and 4 of the years respectively, which are averaged. The attendance data were adjusted to have the identical sample as television, resulting in 158 observations for both television and gate attendance.

I use two empirical models to estimate demand. Each is a linear regression model, the first with time effects, and the second with both time and team effects. I have estimations with and without team fixed effects so I can estimate the effects of variables that are team specific, but the empirical data do not vary over time. Since our sample covers a relatively short period of time (six years) and income data does not vary substantially, I include a model with only time effects to compare the effects and income between attendance and television. The empirical specifications are as follows:

$$\begin{aligned}\ln\left(Att_{v,i,t}\right) &= \beta_1 \ln\left(Price_{i,t}\right) + \beta_2 Win\%_{i,t} + \beta_3 \ln\left(Income_{i,t}\right) + \beta_4 \ln\left(Pay_{i,t}\right) \\ &\quad + \beta_5 NBASUBS_{i,t} + \beta_6 OtherSUBS_{i,t} + \sum_{j=1}^{k} \beta_{6+j} Year_t + \varepsilon_{v,i,t}\end{aligned} \tag{2}$$

$$\begin{aligned}\ln\left(Att_{v,i,t}\right) &= \beta_1 \ln\left(Price_{i,t}\right) + \beta_2 Win\%_{i,t} + \beta_3 \ln\left(Income_{i,t}\right) + \beta_4 \ln\left(Pay_{i,t}\right) \\ &\quad + \beta_5 NBASUBS_{i,t} + \beta_6 OtherSUBS_{i,t} + \sum_{j=1}^{k} \beta_{6+j} Year_t + \sum_{m=1}^{n} \beta_{6+k+m} Team_i + \varepsilon_{v,i,t}\end{aligned} \tag{3}$$

where $Att_{v,i,t}$ is the yearly per capita attendance for viewing method v (gate and television), for team i in year t, *Price* is the weighted average ticket price, *Win%* is the team's winning percentage, *Income* is the city's average income according to the Census Bureau in 2003, *NBASUBS* and *OtherSUBS* are the number of NBA teams and other professional sports teams within the SMSA respectively, *Pay* is the team's payroll, and *Year*[19] and *Team* are fixed effects[20]. Per capita gate attendance is normalized by the standard metropolitan statistical area (SMSA). Given our derivation of TV attendance, deriving per capita estimates allows us to avoid having population in the dependant and independent variables, reducing the likely possibility of contaminating the structure of the errors. For the remainder of the paper I will refer to both gate and TV attendance, assuming it is per capita. The summary statistics are given in table 1.

Empirical Results

The presence of heteroskedasticity and autocorrelation were tested with regard to ordinary least squares. Heteroskedasticity was tested using a Breusch-Pagan/Cook-Weisberg test and was not found to be significant (the hypothesis of constant variance could not be rejected) in the estimation for TV attendance and was found to be significant in the estimation for gate attendance. Autocorrelation was found to be significant in all equations using a Wooldridge test (the hypothesis of no first order-autocorrelation was rejected). Based on these tests, heteroskedasticity and autocorrelation were corrected for using generalized least squares (GLS).

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[19] Fixed effects for each year is included in the estimation, therefore a constant term would make the *X* matrix completely dependent.
[20] This data can be found at rodneyfort.com. All of the data in the sample were originally from USA Today.

Table 2 presents the results of the demand estimations. The results show that consumers who attend the games live are an inherently different group of consumers from fans who watch the games on television. Attending a live game is an all-inclusive event that consumers most likely attend with family and friends and might include other activities, such as dinner. Fans who attend the games live are less sensitive to income, sensitive to the quality of the team (win percent), and sensitive to sports substitutes inside and outside of the NBA. In comparison, fans watching the games on television are more sensitive to income effects, and demand their NBA team to win.

Focusing on the model without fixed effects, I estimated the relationship of income with both television and gate attendance. Income has little-to-no effect on gate attendance, and because consumers generally do not specifically pay to watch local television games, it might be considered a type of quasi-inferior good to television attendance with a negative and significant income elasticity of 1.855. I noted that a longer time span of data might provide better estimates of the income variables since it would be more informative to add these variables to a model with team fixed effects.

For the rest of the variables, I primarily focused on the fixed effects models while making an holistic interpretation from all of the results. Although not significant, the coefficients of the price variables do represent price elasticities. As with most of the sports economics literature, I found that teams price tickets in the inelastic portion of demand, with an estimated elasticity of approximately 0.09. This could be due to behavior factors such as the development of habit formation or additional revenue from concessions or stadium advertising. Consistent with intuition and the income effect previously discussed, higher ticket prices result in greater television demand, evidenced by the positive price elasticity.

In support of other recent findings, both within league and across leagues act as substitute products with the NBA – although more so with gate attendance than with television. I modeled substitution between sports teams as discrete shifts, so the coefficients in the regressions shift demand down. The number of other NBA teams in the market had a negative and significant impact on both television audience and attendance. These results continue to show significant impact of territorial rights that limit the direct competition. With territorial rights firmly entrenched in the market and no reason to think that change is near, research on the effects of indirect substitutes, such as other sports leagues, is an important economic finding. Teams acting as indirect substitutes for other leagues have significant effects on both television and attendance. The substitution effect on attendance is consistent with prior evidence that consumers trade off between professional sports. The substitution effect on television audiences has been previously unexplored and is weaker than gate attendance. This weakness could be because, in the absence of prices, television audiences choose to either watch their NBA team or not, depending on whether they are winning. That is, when consumers do not have to pay for sports, they might be considered fickle.

Payroll effects essentially have no effect on attendance and have an ambiguous effect on television audiences. Both fans who view the game live and fans who view on television have preferences toward the actual quality of the team (win percent) rather than individual talent within the team (payroll).

Perhaps one of the most interesting implications of the results is the difference in consumers' preferences towards winning. Realizing the revenue generated from television is substantial, television audiences' sensitivity toward winning enters into the owners' decision problem and, all else constant, can influence the league's competitive balance. The investment in talent made by team owners depends on the contribution of winning to revenue. With teams in geographical locations with varying revenue potentials, the possibility exists for television audiences' sensitivity for winning to have an effect on competitive balance within the league. Although I am unable to determine the complete marginal revenue of winning from television, the results that I derived do uncover part of the equation: the effects of winning on television demand. From the results, a 1 point increase in a team's win percent increases television attendance by 1.5% and gate attendance by 0.3%.

The difference in sensitivity to winning may also have implications for the effectiveness of revenue sharing programs. Revenue sharing essentially reduces the incentive for owners with higher marginal revenue of winning to invest in talent. Recognizing that winning is more important to television audiences than attendance, these findings have policy implications regarding the effectiveness of the instruments used to improve competitive balance.

CONCLUSION

Because media revenue is such a substantial amount of the revenue that owners generate through team operations and little is currently known about the factors that affect demand, I estimated and compared the results of television and gate demands. While there is undoubtedly much overlap between fans who attend the games and television fans, it appears that fans watching television are an entirely different group than fans who attend games. Fans who watch the games on television are more price sensitive, demand more winning, and do not substitute for other professional sports, compared to fans who attend games. These findings are also an important component of competitive balance.

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TABLES

Table 1. Summary Statistics

Variable	Min	Max	Mean	SD
ln(Gate Attendance)	-2.834	-0.496	-1.486	0.608
ln(TV Attendance)	-1.115	1.881	0.514	0.663
Gate Attendance	0.059	0.609	0.267	0.141
TV Attendance	0.328	6.560	2.041	1.258
ln(Income)	10.217	10.878	10.504	0.141
ln(Payroll)	17.050	18.520	17.832	0.227
Win Percent	0.159	0.817	0.506	0.151
No. NBA Substitutes	0.000	1.000	0.076	0.266
No. Other Substitutes	0.000	6.000	2.278	1.604

Table 2. Demand Estimation for Television and Gate Attendance

	ln(television attendance per capita)				ln(gate attendance per capita)			
	With Time and Team Effects		With Time Effects		With Time and Team Effects		With Time Effects	
	Coefficient Estimates	t-statistics	Coefficient Estimates	t-statistics	Coefficient Estimates	t-statistics	Coefficient Estimates	statistics
price)	0.142	0.55	0.250	1.06	-0.088	-1.27	-0.115	-0.95
income)			1.855***	-2.63			-0.558	-1.08
in Percent	1.521***	5.75	1.354***	5.45	0.332***	4.97	0.263***	3.76
payroll)	-0.282	-1.24	0.071	0.32	0.041	0.72	0.02	0.33
. NBA Subs	1.454***	-5.59	-0.593	-1.54	0.968***	-16.5	0.912***	-4.57
. Other Subs	0.100***	-2.98	0.001	0.02	0.261***	-40.09	0.225***	-6.72
99-00	4.725	1.15	7.224***	2.21	-1.411	-1.39	4.952	0.93
00-01	4.74	1.15	7.142***	2.20	-1.421	-1.39	4.924	0.93
01-02	4.718	1.14	7.115***	2.20	-1.433	-1.41	4.905	0.92
02-03	4.747	1.15	7.048***	2.20	-1.442	-1.41	4.871	0.92
03-04	4.907	1.19	7.200***	2.22	-1.44	-1.41	4.861	0.92
04-05	4.812	1.16	7.070***	2.21	-1.401	-1.37	4.882	0.92
TLANTA	1.116***	-4.70			0.283***	-4.82		
OSTON	0.503***	-4.22			0.544***	-15.21		
HARLOTTE	1.068***	-4.57			0.162	1.11		
HICAGO	-0.084	-0.39			0.293***	-4.74		
LEVELAND	-0.287	-0.83			0.163*	1.95		
ALLAS	-0.352	-1.84			0.074	1.58		
ENVER	-0.319	-1.39			0.493***	9.6		
ETROIT	0.001	0.00			-0.139	-1.94		
OLDEN STATE	-0.281	-1.02			0.828***	10.88		
OUSTON	-0.19	-1.36			-0.57***	-8.76		
DIANA	0.181	1.37			0.268***	7.53		
OS ANGELES	1.644***	6.15			0.366***	6.12		
EMPHIS	0.391***	-2.3			0.277***	6.49		
IAMI	0.677***	-4.86			0.453***	12.5		
ILWAUKEE	-0.308	-1.48			0.298***	6.29		
INNESOTA	-0.351	-1.50			0.144***	2.95		
EW YORK	-1.521	-7.27			-0.063	-1.63		
EW ORLEANS	-0.19	-0.57			0.347***	6.15		
RLANDO	-0.095	-0.42			0.134***	-4.61		
HILADELPHIA	-0.009	-0.06			-0.242	-5.2		
HOENIX	-0.164	-0.93			0.111***	2.99		
ORTLAND	-0.319	-1.03			-0.079	-1.63		
ACRAMENTO	-	-			-	-		
AN ANTONIO	0.283***	2.71			0.13***	2.25		
EATTLE	-0.045	-0.23			0.035	1.22		
ALT LAKE CITY	-0.105	-0.44			0.003	0.39		
ASHINGTON	-0.31	-1.21			0.248***	-3.74		

CHAPTER 4: CONTEST SUCCESS FUNCTIONS AND MARGINAL PRODUCT OF TALENT

Abstract

Although tournaments, conflicts, rent-seeking, and sporting events have been modeled with contest success functions, little empirical support exists for choosing the appropriate form. The difference and ratio forms have been identified by researchers as popular choices to develop theoretical properties and model professional sports leagues. In this article, a multi-stage regression is used to estimate the parameters of difference and ratio forms of the contest success functions. The forms are then compared for best fit using various criteria. The evidence suggests that the ratio form is closest to the true specification. Furthermore, parametric estimates of the ratio form are proved to support the simplifying assumption made by most sports economists that the mass or talent parameter is equal to one. The contest success function is further used to determine the contribution to winning of the candidate players for the 2010 Canadian Men's Olympic Hockey Team.

INTRODUCTION

Empirical economic modeling involves understanding the underlying production process and specifying the appropriate functional forms. Different from traditional production theory, the economics of contests are complicated by the fact that output depends on the relationship between the firms in the industry who are the contestants. A contest is a game in which players increase the probability of winning by exerting effort with the objective of obtaining a prize (Skaperdas, 1996). A contest success function (CSF) describes the production process and the interdependent relationship among the effort of participants and winning. Although the theory of contests and CSFs has progressed forward, substantial empirical analysis is missing. Skaperdas (1996) points out that empirical support for choosing the particular form of the CSF would be a welcome endeavor. This article empirically estimates two forms of the CSF and compares the fit of each model. The analysis is extended to calculate the contribution to winning of the 2010 Canadian Men's Olympic Hockey Team candidate players.

The literature on contests can be divided into three groups: topics, production, and empirical estimation. The economic perspective of contests has been used to describe many different topics including R&D rivalries (Loury (1979), Dasgupta and Stiglitz (1980), Lee and Wilde (1980)), rent-seeking conflict (Tullock (1980), Nitzan (1991), Baye et al. (1993)), political campaigns (Skaperdas and Gorfman (1995)), incentive design (Lazear and Rosen (1981), Green and Stokely (1983), Holmstrom (1982), Nalebuff and Stiglitz (1983), and Rosen (1986)) and sporting events (Fort and Winfree (2009), Rascher (1987), Szymanski (2003, 2004), Szymanski and Kesenne

(2004), Kesenne (2005, 2006)). Economists have also studied the production of contests through strategic commitment (Dixit, 1987), axioms (Skaperdas, 1996), Clark and Riis (1996), Blavatskyy (2008)), incentives (Epstein and Nitzan (2006)), and forms (Jia (2008), Hirshleifer (1989), Cornes and Hartley (2003), Rai and Sarin (2007), Corchon and Dahm (2007)). To the best of the author's knowledge, there is only one paper that empirically estimates CSFs. Hwang (2007) created a Bayesian statistic to compare different logit forms of the CSF using war data and suggests that the ratio form performs best in predicting the probability of winning war battles.

The functional form used to model the underlying process of a production process can change the analytical properties. Currently, there is no consensus about the most appropriate choice of functional form to empirically estimate contest models. The purpose of this article is to compare the properties of two popular functional forms. The data used to estimate the CSF is from the National Hockey League (NHL). Sporting events are a good environment to empirically estimate and test the properties of CSF for three reasons. First, sporting contests produce wins and the structure of each contest is identical and repeated; second, contest-level data are available; and third, winning is a determinant of the owner's profit maximizing objective function[21]. Further, professional sports are a billion dollar industry and proper modeling of sports contests supported with theory will also be of interest to fans, investors, and odds makers. Therefore, the fully parameterized CSF places value on the specific actions that contribute to winning. From a management perspective, placing value on the factors that contribute to winning can be used to determine players' contribution to winning, marginal revenue products, and game strategy decisions. The results are used to calculate the contribution to winning of the

[21] This assumes identical rules for each contest.

players who were being considered for Canada's 2010 Men's Olympic Hockey Team. The approach differs from prior methods previously used in the sports economics literature by imposing a structural model and using contest level data compared to prior methods that do not use and model and season level data.

Evidence suggests that the ratio form of the logit model is a better fit than the difference form of the logit model. The remainder of the paper is as follows: The models are developed and discussed in section 2, the empirical estimation is in section 3, the CSF diagnostics are presented in section 4, the contribution to winning calculation is presented in section 5, and the concluding comments are offered in section 6.

The Model

Consider the owners' profit maximizing function as follows,

$$\pi_{i,g} = R_{i,g}\left(w_{i,g}\left(t_{i,g}, t_{j,g}\right)\right) - C\left(t_{i,g}\right) \tag{1}$$

To ensure positive but decreasing marginal effects of investment in talent on revenue, I assumed the usual conditions $\frac{\partial R_{i,g}}{\partial t_{i,g}} > 0$, $\frac{\partial^2 R_{i,g}}{\partial t_{i,g} \partial t_{j,g}} < 0$. The first order condition is given by,

$$\frac{\partial \pi_{i,g}}{\partial t_{i,g}} = \frac{\partial R_{i,g}}{\partial w_{i,g}} \frac{\partial w_{i,g}}{\partial t_{i,g}} - \frac{\partial C(t_{i,g})}{\partial t_{i,g}} = 0 \tag{2}$$

Where $\pi_{i,g}$ represents team $i's$ profit in game g, R is revenue, w is the probability of a win, t is talent, and $C(\bullet)$ is the cost function. Team $i's$ talent performs actions $t_i \in \mathbb{R}_+$ that increase (or decrease) the probability of winning the game. Therefore, the probability that team i wins the game is $w_i(t_i, t_j)$ where w_i is team $i's$ CSF. The CSF for team i is a function of the talent of both teams. From the perspective of team i, the following usual conditions are assumed, $w_i > 0, \; w_{ii} < 0, \; w_j < 0, \; w_{jj} > 0$.

Different forms of CSFs are used in various areas of the literature. One of the most commonly used forms is the logistic model for its axiomatic properties (see Skaperdas (1996), Arbatskaya and Mialon (2008), Clark and Riis (1998)). Sports economics have focused almost entirely on the ratio form of logit model to describe the effect of talent on winning with little reasoning, other than noting the probability of winning as a function of relative units of talent (see for example Fort and Winfree (2009), Szymanksi (2003)). Further, most sports economists simplify the ratio form by assuming that the mass (or talent) parameter is equal to one without any empirical support. Outside of sports economics, the probit model has been discussed as a viable option. Others have created specific CSFs to describe different situations or to expand on the growing contest literature (see Cochron and Dahm (2008) a survey of the literature).

The conditional logistic model of discrete choice developed by McFadden (1973) has been used in many streams of the economic literature to analyze the factors influencing probable results. Reasons for using the logit model include its foundation in economic theory, ease of econometric estimation, and empirical model fit (Guadagni and Little, 1983). Hirshleifer (1989) points out that ratio form of the logit model has impractical implications in that any investment of zero results in a probability of zero, as long as the opponent invests a small amount of effort. Since in sports the outcome of each game is determined by differences in scoring, the difference form of the logit is a reasonable approach to consider. However, the difference form does not permit for an interior pure strategy Nash equilibrium (Hirshleifer, 1989).

The difference and ratio forms of the logit specification representing the probability of a team $i=1$ win in game g are,

Difference: $w_{i,g} = G_{Diff}(t_{i,g}, t_{j,g}) = \dfrac{\exp\{\gamma t_{i,g}\}}{\exp\{\gamma t_{i,g}\} + \exp\{\gamma t_{j,g}\}} = \dfrac{1}{1+\exp\{-\gamma(t_{i,g} - t_{j,g})\}}$ (3)

Ratio: $w_{i,g} = G_{Ratio}(t_{i,g}, t_{j,g}) = \dfrac{t_{i,g}^{\lambda}}{t_{i,g}^{\lambda} + t_{j2,g}^{\lambda}} = \dfrac{1}{1+\exp\{-\lambda(\ln t_{i,g} - \ln t_{j,g})\}}$ (4)

where γ and λ are the mass-parameters affecting the shape of player $i's$ CSF.

$w_{j,g} = 1 - w_{i,g}$.

There are 2 primary differences between the difference and ratio form of the CSF: (1) the underlying assumption imposed on the data, and (2) the shapes of the CSF. The difference form does not consider the absolute value of the number while the ratio form does. For example, in the case of hockey, the difference between 3 and 4 shots is 1 and the ratio is 0.75, while the difference between 5 and 6 shots remains 1 while the ratio changes to 0.83. In this case, the difference and ratio forms yield different results. Similar to any model, the results are constrained by the underlying assumptions of the functional form imposed. The difference form of the CSF has increasing returns to the point where $\pi = 0.5$ and diminishing returns thereafter. The ratio form has this same characteristic as long as $\lambda > 1$. However if $\lambda \le 1$, the ratio form has diminishing returns to effort throughout (Hirshleifer, 1989), although in both cases the greater the mass-parameter the more the input contributes to winning. Since the theory does not suggest the best choice of the CSF, I estimated and compared the results of both the difference and ratio forms of the logit model.

Empirical Estimation

Many of the statistics regularly used to measure productivity are weak measures of the underlying production process. In hockey, the number of shots on goal is a common statistic used to measure the amount of offensive scoring chances generated. However, every shot on goal is different, creating different levels of quality of scoring chances. For example, a wrist shot taken from 20 feet most likely has a different probability of resulting in a goal than a backhand taken from 40 feet. Using the same logic, players' shooting percentages and goaltenders' save percentages used to measure a player's ability to score and a goaltender's ability to make a save are inaccurate.

Play-by-play game data were collected for NHL games from the 2008-09 season from nhl.com. The data contains detailed shot information as well as whether the shot resulted in a goal. The shot information includes the following shot characteristics: shot-type, length, advantage type, and time of shot. The player taking the shot and the goaltender attempting to stop the shot are also included in the data. With this data, a multi-stage recursive system is used to create more accurate measures representing the underlying production process and estimating the parameters of the CSFs. The first stage calculates the predicted probability that a shot will result in a goal, given certain shot characteristics. The second stage uses the predicted probability from the first stage as an instrument for shot quality, and then re-predicts the probability that a shot results in a goal, given the shot quality, as well as player and goaltender characteristics. The third stage uses the predicted values from the second stage to estimate the parameters of the CSFs.

The following takes place in stage 1. Shots are differentiated by predicting the probability that each shot taken will result in a goal given certain shot characteristics. The empirical estimation for the probability that a shot resulting in a goal given certain shot characteristics is,

$$Pr(Isgoal_s = 1) = F(shot\ characteristics_s, error_s) \tag{5}$$

$F(\cdot)$ is the logistic distribution function, $isgoal_s$ is an indicator variable equaling 1 if shot s resulted in a goal and 0 otherwise. The shot characteristics are shot-type (deflected, tip-ins, wrap-arounds, wrist, slap, snap, and backhand), shot length (distance in feet from the goal). Shot-types are further differentiated by defining rebounds as shots taken within 5 seconds of the previous shot. The predicted probability is a measure of shot quality.

Then, using the predicted probabilities from stage 1 as a measure of shot quality, stage 2 predicts the probability that a shot results in a goal by incorporating players' ability to score and goaltenders' ability to make saves into the model. Whether from differences in shot strength, accuracy, superior positioning, and/or other (sometimes unobservable) characteristics, players have differing abilities to score goals. Similarly, goaltenders have differing abilities to stop shots from becoming goals. The empirical estimation for the probability that a shot results in a goal is further specified as,

$$tgs_s = Pr(Isgoal_s = 1) = F(isgoalstage1_s, player\ char, goaltender\ char, error_s) \tag{6}$$

where $isgoalstage1$ is the predicted probability from stage 1. The variable $player\ char$, stands for player characteristics, indicator variables grouping players on a projected goal per season basis (e.g. 0-4 goal scorer, 5-9 goal scorer) are used as a proxy for a player's ability to score[22]. The variable *goaltender char* , represents goaltender characteristics, and is an indicator variable identifying the specific goaltender attempting to stop the shot. The estimated probability from (6) is different from (5) in that it accounts for players' and goaltenders' contributions to shots becoming goals and only differentiates shots by level of quality, not by their individual shot characteristics.

Empirical Results from Stage 1 and 2

In addition to the summary statistics in table 1, figures 1a to 1g show the percentage of shots resulting in goals by each length group (5 feet) for each shot type, for both traditional shots and rebounds. Not evident in the graphs is the relative infrequency of rebound shots for deflected, tip-ins, and wrap-around shots. Noticeable from the figures, the functional relationship between the probability that a shot results in a goal and shot length is not necessarily linear or significant for all shot types. Therefore, the empirical model was specified by observation and testing for significance of both the linear and inverse length relationship as well as slope and shift effects of rebounds. Empty net goals, penalty shots, shots taken from outside the offensive zone, and 64 erroneous data entries were eliminated[23]. Therefore, the sample consists of 67,441 shots that resulted in 7,024 goals.

The logistic regression results from (5) are presented in table 2. Deflections are modeled with an intercept and inverse in length slope effect, wrap-arounds with an intercept effect, tip-ins with an intercept and linear in length slope effect, and wrist, slap,

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[22] Projected goals per season = $\frac{\text{goals}}{\text{games played}} \times 82$

[23] Removing shots taken from outside the offensive zone assumes that these shots were not legitimate attempts at scoring. The offensive zone is 60 feet from the goal-line.

snap, and backhands are modeled with an intercept and inverse in length slope effects with a shift effect for rebounds. Power-play and short-handed are modeled as shift effects.

All of the estimates are significant at the 1% level with the exception of the length of tip-ins which is significant at the 10% level. With the inverse length relationship, the predicted values from the logistic regression approaches 1 very quickly as length approaches 0. Since only 1.4% of all shots were from less than 5 feet, a floor of 5 feet is placed on all shots limiting their predicted values. Table 3 summarizes the predicted probability that an even-strength shot results in a goal for each shot-type taken, various shot lengths: 20, 40, and 60 feet, as well as each shot-type's mean length. At their mean lengths, in decreasing order, the shot types of traditional shots that have the greatest to least probability of resulting in a goal are: tip-ins, deflections, backhands, snaps, wrap-arounds, wrists, and slaps. The predicted values of an even-strength shot from (3) of each shot-type are included in the graphs in figures 1a-1g. The probability of scoring on slap, snap, and wrist shots increases at a substantially increasing rate from approximately 20 feet to 5 feet.

The logistic regression results from (6) and their marginal effects are in table 4. All of the variables are significant at the 1% level. A check of the validity of $isgoalstage1$ as a proxy for shot quality in (4) is the predicted probability holding the player and goaltender characteristics constant should be 1; it is 0.998[24]. The player characteristic 0-4 goal scorer is dropped in the regression, avoiding collinearity and making the other goal scoring categories relative to a 0-4 goal scorer. There were

[24] The predicted probability is calculated as follows: $\left(1+\exp(-6.25)\right)^{-1} = 0.998$.

66,579 observations. Figure 2 is the theoretical goals scored (tgs) calculation for each group of goal scorers for different levels of shot qualities against the average goaltender[25]. Generally, the shift effect between goal scorer groupings increases. The grouping of 45-49 goal scorer increases substantially, as it is primarily comprised of 2 pure goal scorers, Danny Heatly and Jeff Carter. The 50+ grouping actually decreases to below the 30-34 grouping, indicating that the increased number of goals scored by players in this category results from factors other than superior shooting abilities. There are 84 goaltender indicator variables representing relative levels of decreased shift effect in the probability that shot results in a goal. Figure 3 is the tgs calculation for 2 of the 84 goaltenders for different levels of shot quality against a 10-14 goal scorer, Tim Thomas and Jose Theodore. The 3 goaltenders that were the most (least) effective at decreasing the probability that a shot resulted in goal were: Daniel Lacosta, Tim Thomas, and Brian Boucher (Brent Krahn, Justin Pogge, James Howard). Daniel Lacosta played in only 2 games during the 2008-09 season and he had 1 shut-out. Tim Thomas was awarded the Vezina Trophy for the goaltender who is judged to be the best at this position, an award voted on by the league's general managers. The summary statistics are presented in table 5[26]. Figure 4 is a histogram summarizing the distribution of theoretical goals scored from (4), the predicted probability that a shot results in a goal given the shot quality, and player and goaltender characteristics. Section 5 includes an example of how the marginal effects are used to calculate players' contribution to winning.

[25] The average goaltender is defined as the average of the goaltenders coefficients which equals -3.15.
[26] The summary statistics for goaltender indicators are not included and are available upon request.

Empirical Results of Stage 3: The Contest Success Function

Both the difference and ratio form of the CSFs are estimated. In the second stage of the regression system, tgs_s was calculated as predicted probability that shot s results in a goal given the shot quality, and player and goaltender characteristics. Therefore, the aggregate tgs_s for each team i in game g is $TGS_{i,g} = \sum_{s=1}^{S} tgs_{i,g,s}$. Therefore, the empirical specification for the CSF that team i wins game g is,

$$w_{i,g} = G(TGS_{i,g}, TGS_{j,g}, home_g,\ constant, error_g) \tag{7}$$

$G(\cdot)$ is specified by (3) and (4). $home_g$ is an indicator variables equaling 1 if team i played game g at home and 0 otherwise. Each game is played from 2 perspectives: team i or team j being the home team. Therefore, each game is included twice in the sample, once with team i being the home team and once with team j being the home team.

In the 2008-09 NHL season, games tied at the end of regulation time were settled via a 5 minute sudden death overtime period or a shootout. Overtime is a 5 minute additional period played at the end of regulation. The rules during overtime change slightly as each team plays with 4 skaters compared to 5 during regulation time. Also, the game is won if either team scores in overtime. Although Banerjee, Swinnen and Weersink (2004) find that teams play more aggressively during overtime play, regulation and overtime play is not differentiated because, although teams may play more aggressively, TGS along with player and goaltender characteristics remain the factors that contribute to winning. However, the factors that contribute to winning through a shoot-out win are fundamentally different than both regulation and over-time play and are therefore omitted from the sample. During the 2008-09 season there were 1,230 NHL games. There were 17 games where I was unable to obtain the play-by-play reports and 151 games in my sample where outcome of the game was decided in a shoot-out, resulting in 2,124 data observations.

The summary statistics are in table 6. The logistic regression results and their marginal effects are in table 7. The parameter estimates determine the degree that talent affects winning for their respective models and is what Fort and Winfree (2009) referred to as a talent parameter. The estimates for the talent parameters and home-ice advantage are significant at the 1% level in both forms of the CSF. The estimates for the talent parameters are 0.314 and 1.027 in the difference and ratio forms respectively. These are the values which have not been previously estimated. Supporting the simplifying assumption made by most sports economists that $\lambda = 1$, I was not able to reject the null hypothesis that $\lambda = 1$[27]. Home-ice advantage increases the probability of a win by 8.0%.

Figure 5 graphs the CSFs with the home-ice advantage removed by setting $home = 0.5$. Specifically, it is the graph of the probability of a win for different values of TGS_1 between 0 and 6, holding TGS_2 constant at 3.00. In both forms $TGS_i = TGS_j$ results in $w_i = w_j = 0.5$. The CSFs are shifted from home ice-advantage. The marginal effects are non-linear. Figure 6 shows the marginal effects that correspond with the CSFs in figure 5. At $TGS_i = TGS_j$, the marginal probability of an additional TGS_i are 7.9% and 8.6% in the difference and ratio form respectively. Deviating from the point where

[27] The p-value was 0.7871.

$TGS_1 = TGS_2$ results in symmetrical changes in the marginal probabilities in the difference form and asymmetrical changes in the ratio form.

The ratio form places more value on marginal increases in TGS for smaller values compared to larger values. The ratio form also has greater variation in its marginal probabilities than does the difference form. For example, the marginal probabilities of a 1 unit deviation from 3.00 in each direction results in marginal probabilities of winning of 12.3% when $TGS_i = 2.00$ and 6.3% when $TGS_i = 4.00$, an increase and decrease of 3.7% and 2.8% respectively. The corresponding marginal probability in the difference model is 7.7% when $TGS_i = 2.00$ and when $TGS_i = 4.00$ for an increase and decrease of 0.2%. The shapes of the two CSFs are noticeably different, supporting the need for testing the model that best fits the data. Although difficult to see, the difference form is a slightly S shaped curve with a point of inflection compared to ratio form that has decreasing returns throughout.

CSF Regression Diagnostics

Models are fitted to the data in an effort to understand the underlying process. The relationship between the theoretical construct of the CSFs and the structure of the models are tested 3 ways: classification tables, goodness-of-fit measures, and specification. Fortunately, there are sufficient data to re-estimate the parameters and to create a validation sample to test the out-of-sample properties. The classification tables and some of the goodness-of-fit measures are tested in and out-of sample. The specifications of the models are compared for best fit using a likelihood ratio test for non-nested models.

Classification Tables

Classification tables can be used to evaluate the predictive accuracy by cross-classifying the observed and predicted values based on a cut-off point. The cut-off point of probability = 0.5 is chosen. The stratified sampling technique described above was used to choose whether team $i = 1$ or team $i = 2$ is allocated as the home team. The in-sample classification tables are in table 8. In-sample, there is virtually no difference across CSF forms. The models correctly classify between 62.1% in both forms. The prediction properties within each classification table are also similar across models. Both forms predict 61.1% of wins and 63.3% of losses successfully.

The out-of-sample classification tables are in table 9. The out-of-sample properties are derived by re-estimating the coefficients with the first 1,600 observations and predicted onto the final 262 observations. Owing to the change in sample sizes, it is only relevant to compare across models, not across samples. The out-of-sample properties are very similar across forms as well. The models correctly classified 64.9% and 66.0% in the difference and ratio forms respectively. The difference and ratio forms predict 64.1% and 65.5% of wins and 65.8% and 66.7% of losses successfully respectively. Generally, neither form of the model performs better in-sample or out-of-sample than the other.

Although the classification tables are an appealing way of summarizing the results of the models, shortcomings exist. Classification tables do not address the structural properties of the errors. Specifically, information is lost about the distance of errors through mapping the continuous fitted values to a set of dichotomous variables (Hosmer and Lemeshow, 2000). Generally, goodness-of-fit tests measure that the distance between the predicted and observed values is small and unsystematic.

Goodness-of-fit

Many different fit measures have been suggested for discrete choice models. Without simply reporting a myriad of test statistics, I chose from a series of measures to compare the fit of the difference and ratio forms of the model. Specifically, I calculated the Hosmer-Lemeshow statistic (in-sample and out-of-sample) (Hosmer and Lemeshow, 2000), McFadden's (1974) likelihood ratio index (LRI), the Akaike information criterion (AIC) (Akaike, 1973), and the Bayesian information criterion (BIC) (Schwarz, 1978).

The Hosmer-Lemeshow statistic tests the structure of the errors by creating ordered groups based on their estimated probability and then comparing the number observed to predicted (Hosmer and Lemeshow, 2000). The Hosmer-Lemeshow statistic is,

$$G_{HL}^2 = \sum_{j=1}^{10} \frac{O_j - E_j}{E_j(1 - E_j / n_j)} \sim \chi_8^2 \qquad (8)$$

where n_j is the number observations in the j^{th} group,

$O_j = \sum_i y_{ij} =$ Observed number of cases in the j^{th} group,

$E_j = \sum_i p_{ij} =$ Expected number of cases in the j^{th} group.

The in-sample and out-of-sample Hosmer-Lemeshow statistics are presented in tables 10 and 11, respectively[28]. Both in-sample and out-of sample, the Hosmer-

[28] The same out-of-sample method was used as in the classification tables.

Lemeshow statistics were unable to reject the null hypothesis of a lack of fit model in both forms of the model. The probability of rejecting the null hypothesis in-sample was 0.78 and 0.12 and out-of-sample was 0.28 and 0.18 in the difference and ratio forms respectively. The computation of the Hosmer-Lemeshow statistic for the validation set follows directly from (6) with the appropriate substitutions (Hosmer and Lemshow, 2000). The disadvantage of the Hosmer-Lemshow test is that deviations from fit can be missed in the grouping process. Therefore, other goodness-of-fit measures are performed.

The results of McFadden's LRI, and the AIC and BIC are in table 12[29]. McFadden's (1974) LRI is an analog to the R^2 calculation in a conventional regression. The index is bounded between 0 and 1 and increases as the model improves. Information criteria can be used to make comparisons across models. To use information criteria as a method to compare models the likelihoods must be conformable. Therefore, since the events across the models are the same in this case, information criterion is a particularly valuable method of model comparison. AIC minimizes the estimated prediction risk, and BIC uses a Bayesian perspective to maximize the posterior probability of a model. Generally, BIC chooses the true model and AIC minimizes the risk of error. Given two models fit on the same data, the model with the smaller value of the information criterion is considered to be better. There is little difference between the two forms of the model by McFaddens LRI or AIC. However, the difference between the BIC of two models is 10.828, in favor of the ratio form. According to Raftery (1996), this provides very strong evidence in favor of the ratio form of the model.

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[29] Since McFadden's LRI, and the AIC and BIC are more popular goodness-of-fit measures, their formulas are not presented in the paper. See the following references for the specific formulas. McFadden's LRI: Greene (2003, pg. 683), AIC: Greene (2003, pg. 160), pg. 512, BIC: Greene (2003, pg. 160).

The models are non-nested in terms of functional forms. Vuong's (1998) likelihood ratio test determines the appropriate choice between rival non-nest models. One model is preferred over another if the individual log-likelihoods of the models are significantly larger than the log-likelihood of the rival model. The null hypothesis is,

$$H_o : E_o\left[ln \frac{f_{diff}\left(y_i | x_i ; \gamma\right)}{f_{ratio}\left(y_i | x_i ; \lambda\right)} \right] = 0 \tag{9}$$

which states that the 2 models are equal close to the true specification. The test statistic is,

$$V = \frac{\sqrt{n}\left(\frac{1}{n}\sum_i^n m_i\right)}{\sqrt{\frac{1}{n}\sum_i^n \left(m_i - \overline{m}\right)^2}} \sim N\left(0,1\right) \text{ where } m_i = ln\frac{f_{diff}\left(y_i | x_i ; \gamma\right)}{f_{ratio}\left(y_i | x_i ; \lambda\right)} \text{ and } \overline{m}_i = \frac{1}{n}\sum_i^n m_i \tag{10}$$

where, $f_{diff}\left(y_i | x_i ; \gamma\right)$ is the probability density function of the difference form and $f_{ratio}\left(y_i | x_i ; \lambda\right)$ is the probability density function of the ratio form[30]. Positive and significant values imply that difference form is favored over ratio form, while negative and significant values imply ratio form is favored over the difference form. Using the same stratified sampling technique, the Vuong statistic is -2.43 resulting in a p-value of 0.012, rejecting the null hypothesis at the 5% significance level. The Vuong likelihood ratio test for non-nested models finds evidence that the ratio form is closer to the true specification than the difference form.

Classification tables, McFadden's LRI, and the AIC criterion show little evidence of differences in the prediction capabilities or the goodness-of-fit between the difference

[30] The probability density function is: $f_i\left(y_i\right) = \pi_i^{y_i}\left(1 - \pi_i^{1-y_i}\right)$, $y_i = 1$ (win) and $y_i = 0$ (loss)

and ratio forms of the logit specification. However, the BIC and Vuong likelihood ratio find statistical evidence that the ratio form is closer to the true specification than the difference form.

The Marginal Product of Talent and Contribution to Winning

Professional sports are a multi-billion dollar industry. Forbes (www.forbes.com) reports that the Toronto Maple Leafs Hockey Club alone was worth $470 million in 2009. Given teams produce wins, winning is one of the key factors that contributes to demand and revenues (Fort, 1996). Therefore, determining methods of calculating players' contribution to winning is a worthwhile endeavor. The first empirical estimation studying the production process in sports was pioneered by Scully (1974). By using season-level data, he determined baseball players' marginal contributions to winning and then extended it to calculate players' marginal revenue product. Others (Scully, 1989; Zimbalist, 1992) have extended Scully's 1974 work, but none have fundamentally changed or improved the method of determining players' contributions to winning. Empirical estimation of the CSF places value on the inputs that contribute to winning and therefore provides a nice framework for calculating each player's contribution to winning.

An Example: The 2010 Canadian Men's Olympic Hockey Team

On October 18, 2008, Hockey Canada announced the Men's Olympic Management Staff that would choose the team to compete in the 2010 Olympic Winter Games hosted by the cities of Vancouver-Whistler, Canada. Steve Yzerman was named the Executive Director. From August 24-28, 2009 Hockey Canada hosted a team orientation camp in Calgary Alberta. Invited to the orientation camp were 46 candidate players competing to represent Canada at the Olympics. On December 30, 2009, the Men's Olympic Management Staff announced the 23 players (3 goaltenders, 7 defenseman, and 13 forwards) chosen to represent Canada at the Olympics. All of the players chosen (with the exception of Patrice Bergeron) were invited to the orientation camp. The announcement of the team received national television coverage in Canada and international print media coverage.

The ratio form of the CSF is used to calculate the amount that each of the candidate players contributed to winning in the 2008-09 season and up to December 30th in the 2009-10 NHL season. Each player contributes to winning through the factors determined by the CSF. For simplicity, even-strength play is the focus of the analysis. The contribution of each player (skater) p at time t is calculated in the following way,

$$CW\ of\ \ player_{p,t} = \begin{cases} \left(\left(\frac{1}{5}\frac{1}{G}\sum_{g=1}^{G}\sum_{s=1}^{S} tgsf_{s,p,t} \right)\left(1 + \frac{\partial tgs}{\partial player_{p,t}} \right) - \left(\frac{1}{5}\frac{1}{G}\sum_{g=1}^{G}\sum_{s=1}^{S} tgsa_{s,p,t} \right) \right)\left(\frac{\partial w}{\partial TGS} \right), \text{if } \frac{\partial tgs}{\partial player_{p,t}} \text{ is signficant} \\ \left(\left(\frac{1}{5}\frac{1}{G}\sum_{g=1}^{G}\sum_{s=1}^{S} tgsf_{s,p,t} \right) - \left(\frac{1}{5}\frac{1}{G}\sum_{g=1}^{G}\sum_{s=1}^{S} tgsa_{s,p,t} \right) \right)\left(\frac{\partial w}{\partial TGS} \right), \text{ otherwise} \end{cases} \tag{11}$$

The equation has 2 parts: offensive contribution and defensive contribution. The first half, the offensive contribution, is the increase in the probability of a win as a result of the theoretical goals scored while player p was on the ice. $tgsf_{s,p,t}$ is theoretical goals scored for, calculated by (4) for every shot s when player p is on the ice at time t[31].

The division by 5 equally distributes the $tgsf$ to every player on the ice at the time shot s was taken. The summation and division by G normalizes all players to an average contribution per game. $\frac{\partial tgs}{\partial player_{p,t}}$ is the increased shift in the probability that any shot taken from player p results in a goal. $\frac{\partial w}{\partial TGS}$ is the marginal probability of a TGS discussed in section 3.2. t denotes either the 2008-09 season or the first part of the 2009-10 NHL season.

The second half, the defensive contribution, is the decrease in the probability of a win as a result of theoretical goals given up to the opposition while player p is on the ice. $tgsa$ is defined as theoretical goals scored against.

Equation (11) equally distributes the contribution to winning of every $tgsf$ and $tgsa$ to every player on the ice at the time a scoring chance is generated or given up. The number of shots taken is also evenly distributed. This is not a perfect method for determining players' contributions to winning because it slightly under-estimates the contribution to winning of above average players and over-estimates the contribution to winning of below average players. However, it does account for unobservable behaviors performed by players. Over time, as more combinations of players play together, the spread in the contribution to winning between more and less skilled players will increase accordingly. The method also provides an alternative perspective of players' contribution to winning. Improving on the model to account for the between effects of players is an area for future research.

[31] I slightly abuse notation and use t to stand for time as well as talent.

Different from skaters, goaltending is primarily a one-dimensional position. Goaltenders contribute to winning by decreasing the probability that a shot results in a goal. Therefore, the contribution to winning of each goaltender q at time t is calculated in the following way,

$$CW\ of\ goaltender_{q,t} = -\frac{\partial tgs}{\partial goaltender_{q,t}} \frac{\partial Pr(win)}{\partial TGS} \tag{12}$$

where $\frac{\partial tgs}{\partial goaltender_{q,t}} < 0$ so that (12) can be interpreted as a decrease in the probability of winning of goaltender $q's$ opponent due to goaltender $q's$ ability to prevent shots from becoming goals. For (10) to have the same interpretation as (11), the negative changes the interpretation to the increase if the probability of winning of goaltender $q's$ own team wins.

5.1 Empirical Estimation and Contribution to Winning Calculation

Some of the variables in (9) and (10) are determined in this paper. The average TGS in a game was 3.17. The marginal probability of TGS on winning that is used, 8.6%, is the marginal effect from the ratio form when $TGS_1 = TGS_2$. The average theoretical goals for and against the candidate players are presented in table 14. The $tgsf_{s,p,t}$ is calculated using the average goaltender and 0-4 goal scorer coefficients and $tgsa$ is calculated with the average goaltender and 10-14 goal scorer coefficients for 2008 and

2009[32 33 34]. The values of $\frac{\partial tgs}{\partial player_{p,t}}$ and $\frac{\partial tgs}{\partial goaltender_{q,t}}$ are estimated the following way,

$$tgs_{s,t} = Pr(Isgoal_{s,t} = 1) = F\begin{pmatrix} isgoalstage1_{s,t}, TC\ Cand\ Player\ Char_t, \\ Other\ Player\ Char_t, \\ TC\ Cand\ \ Goaltender\ Char_t, \\ Other\ Goaltender_t, error_t \end{pmatrix} \quad (13)$$

Equation (13) is similar to (6) in that it captures shot quality, players' ability to score goals and goaltenders' ability to make saves. *TC Cand Char* stands for Team Canada candidate characteristics and are indicator variables. *Other* is all other than the candidate players. The logistic regression results are in table 13. There are 100,222 observations[35].

The contribution to winning is calculated in table 14. Expressed as a percentage, the contribution to winning is the increase (decrease) in the probability of a win resulting from each player's play during both the 2008-09 season and the 2009-10 season. The column labeled 2010 Men's Olympic Hockey Team Member indicates whether the player was chosen to be on the Olympic team[36]. Using the 2009 model rankings, the top 3 goaltenders were chosen, 10 of the top 13 forwards, and 5 of the top 7 defensemen were

[32] The "average goaltender" is consider to have the average of the goaltender coefficients from (4); -3.15.

[33] 0-4 goal scorer coefficients is used because the player effects determined by $\frac{\partial tgs}{\partial player_{p,t}}$ act as a shift effect from the 0-4 goal scorer.

[34] 10-14 goal scorer coefficient is used because that is the closest group of the average goal scorer. See the summary statistics in table 5.

[35] The summary statistics are available upon request.

[36] The final team that represents Canada at the Olympics could be different due to injuries.

chosen[37]. Of course, the results can be used to measure individual player's offensive and defensive capabilities for game strategy decisions and player trends over time.

Concluding Comments

The underlying production process of contests is different than traditional production theory because the output of a single firm is intrinsically connected to the output of the other firms in the industry. Although improvements have been made in the way of theoretical advancement in the study of contests, little supporting empirical work currently exists. Functional forms are of particular interest because they impose assumptions about the process that may significantly affect results.

In this paper, National Hockey League data is analyzed to estimate and test the fit of the difference and ratio forms of the logistic model of the contest success function. Using a multi-stage regression system, I created a statistic called theoretical goals scored (tgs) and compared the prediction accuracy, goodness-of-fit, and specification of the difference and ratio forms. Using the best form of the model is important because the shape and marginal effects of each contest success function is different. Evidence suggests that the ratio form is a better fit compared to the difference form. The ratio form is of particular interest to sports economists that make simplifying assumptions in their league models. The results of this article support their assumption that the talent parameter in the ratio form is equal to one.

Since estimating the parameters of the contest success functions places value on the inputs that contribute to winning, contribution to winning calculations are a possible extension. An example is provided using the candidate players from the 2010 Canadian

[37] I recognize that other factors are used in deciding team members than contribution to winning.

Men's Olympic Hockey Team. Of the candidate players, Martin Brodeur (goaltender), Jonathan Toews (forward), and Chris Pronger (defense) contributed the most to winning at their respective positions during the first part of the 2009-10 NHL season. Each of these players was selected to be a member of the 2010 Olympic Team. Cam Ward (goaltender), Ryan Getzlaf (forward), and Mike Green (defense) were the top contributors during the 2008-09 season. Ryan Getzlaf was the only one of these players selected. Team managers can use the information enclosed in the regressions and summary statistics for many different types of game and personnel decisions.

Extensions to this research are plentiful. Estimating other forms of the contest success functions and testing their fit is an obvious route. Also, accounting for heterogeneity across contestants may give insight into the factors that affect winning a contest. Unobservable heterogeneities may exist in both a contestant's ability to win (intercept) and their response to the covariates (slope). It is beyond the scope of this article, but the contribution to winning model can be enhanced by incorporating between player effects and stage 1 and 2 of the regression can be modeled in different ways.

With the advances in the theoretical development of contest success function and the wide range of production processes that have contest like behaviors, equal advances in empirical modeling are important. This paper provides a jumping-off point for researchers to build a foundation of empirical support describing the underlying process of contests.

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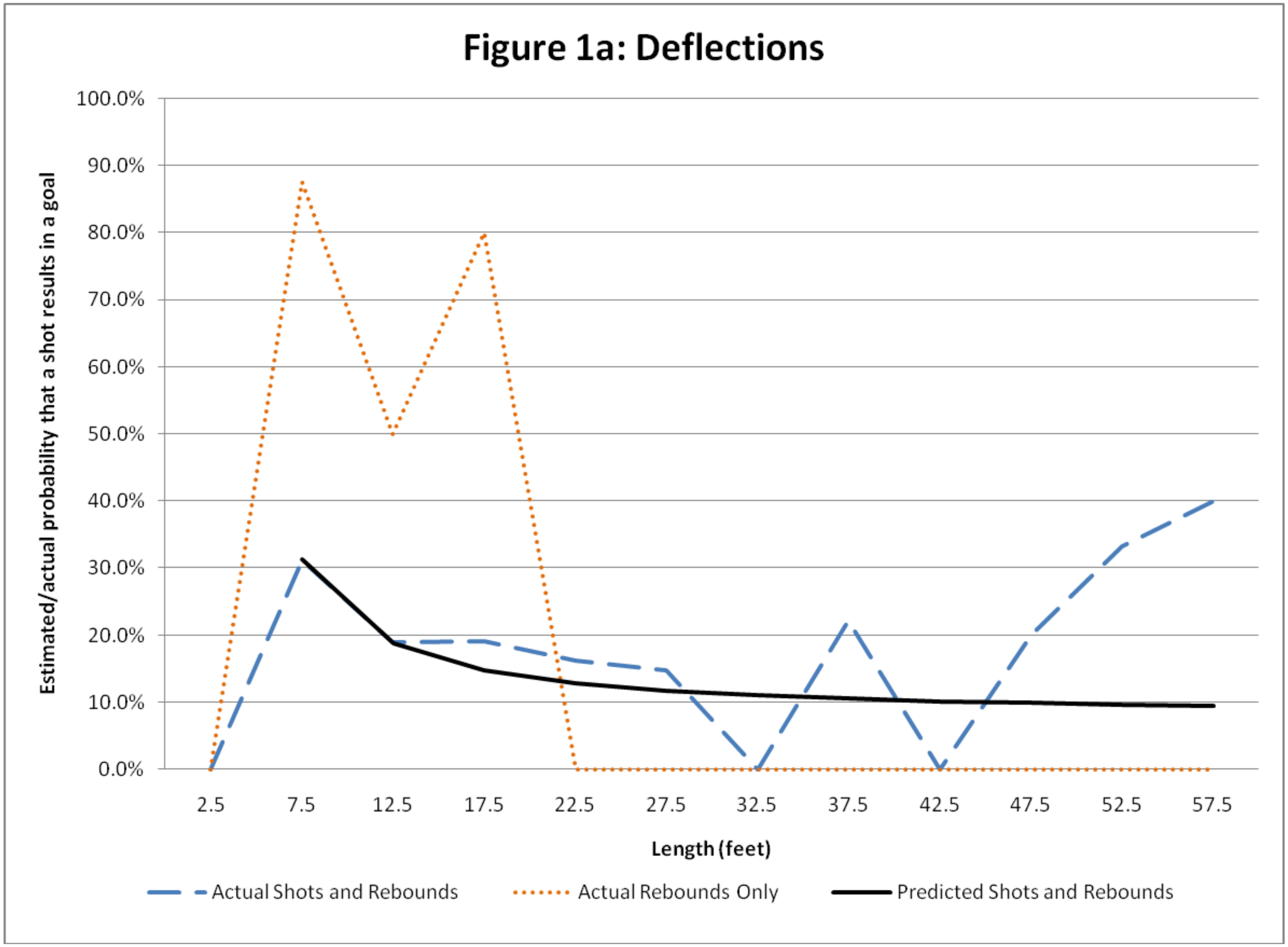
TABLES AND FIGURES

Table 1. Summary statistic of shot characteristics.

Shot type and advantage type(indicator variables)						Shot length (continuous variables)			
Variable	Count	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Traditional shots that did not result in a goal (no. obs. = 63354)									
Deflected	625	0.011	0.105	0	1	15.869	7.290	5	57
Tip	2544	0.045	0.208	0	1	15.351	6.352	3	59
Wrap-around	902	0.016	0.125	0	1	8.367	3.323	2	41
Slap	12979	0.230	0.421	0	1	46.534	10.244	4	59
Snap	9235	0.164	0.370	0	1	34.389	12.671	4	59
Wrist	25609	0.454	0.498	0	1	31.682	13.932	0	59
Backhand	4519	0.080	0.271	0	1	18.924	9.588	2	59
Power-play	10778	0.191	0.393	0	1	na	na	na	na
Short-handed	1534	0.027	0.163	0	1	na	na	na	na
Even-Strength	44101	0.782	0.413	0	1	na	na	na	na
Rebound shots that did not result in a goal (no. obs = 4174)									
Deflected	12	0.003	0.055	0	1	19.333	10.671	10	47
Tip	191	0.048	0.214	0	1	12.314	4.547	5	38
Wrap-around	50	0.013	0.111	0	1	7.920	3.361	3	18
Slap	433	0.109	0.312	0	1	41.106	16.005	6	59
Snap	447	0.112	0.316	0	1	23.559	13.540	4	59
Wrist	2152	0.542	0.498	0	1	17.842	10.961	3	59
Backhand	318	0.080	0.271	0	1	13.311	5.340	0	45
Power-play	850	0.214	0.410	0	1	na	na	na	na
Short-handed	79	0.020	0.140	0	1	na	na	na	na
Even-Strength	3045	0.766	0.423	0	1	na	na	na	na
Traditional shots that did result in a goal (no. obs. = 5748)									
Deflected	152	0.028	0.164	0	1	14.980	8.674	6	59
Tip	624	0.114	0.318	0	1	14.917	7.525	4	57
Wrap-around	57	0.010	0.101	0	1	8.018	3.399	2	24
Slap	855	0.156	0.363	0	1	41.389	13.066	5	59
Snap	918	0.167	0.373	0	1	25.824	11.695	2	59
Wrist	2345	0.427	0.495	0	1	21.913	11.704	2	59
Backhand	535	0.098	0.297	0	1	13.884	6.439	0	57
Power-play	1541	0.281	0.449	0	1	na	na	na	na
Short-handed	191	0.035	0.183	0	1	na	na	na	na
Even-Strength	3754	0.684	0.465	0	1	na	na	na	na
Rebound shots that did result in a goal (no. obs=1516)									
Deflected	16	0.010	0.101	0	1	11.875	3.897	7	20
Tip	97	0.063	0.243	0	1	12.330	5.484	5	41
Wrap-around	14	0.009	0.095	0	1	6.714	1.939	4	9
Slap	88	0.057	0.232	0	1	27.375	17.089	3	59
Snap	159	0.103	0.305	0	1	18.673	9.491	4	59
Wrist	897	0.583	0.493	0	1	14.074	6.907	0	57
Backhand	267	0.174	0.379	0	1	12.419	4.863	0	44
Power-play	349	0.227	0.419	0	1	na	na	na	na
Short-handed	38	0.025	0.155	0	1	na	na	na	na
Even-Strength	1151	0.748	0.434	0	1	na	na	na	na

Figure 1a to 1f: Percentage of shots that resulted in goals by each length group for both actual and predicted values



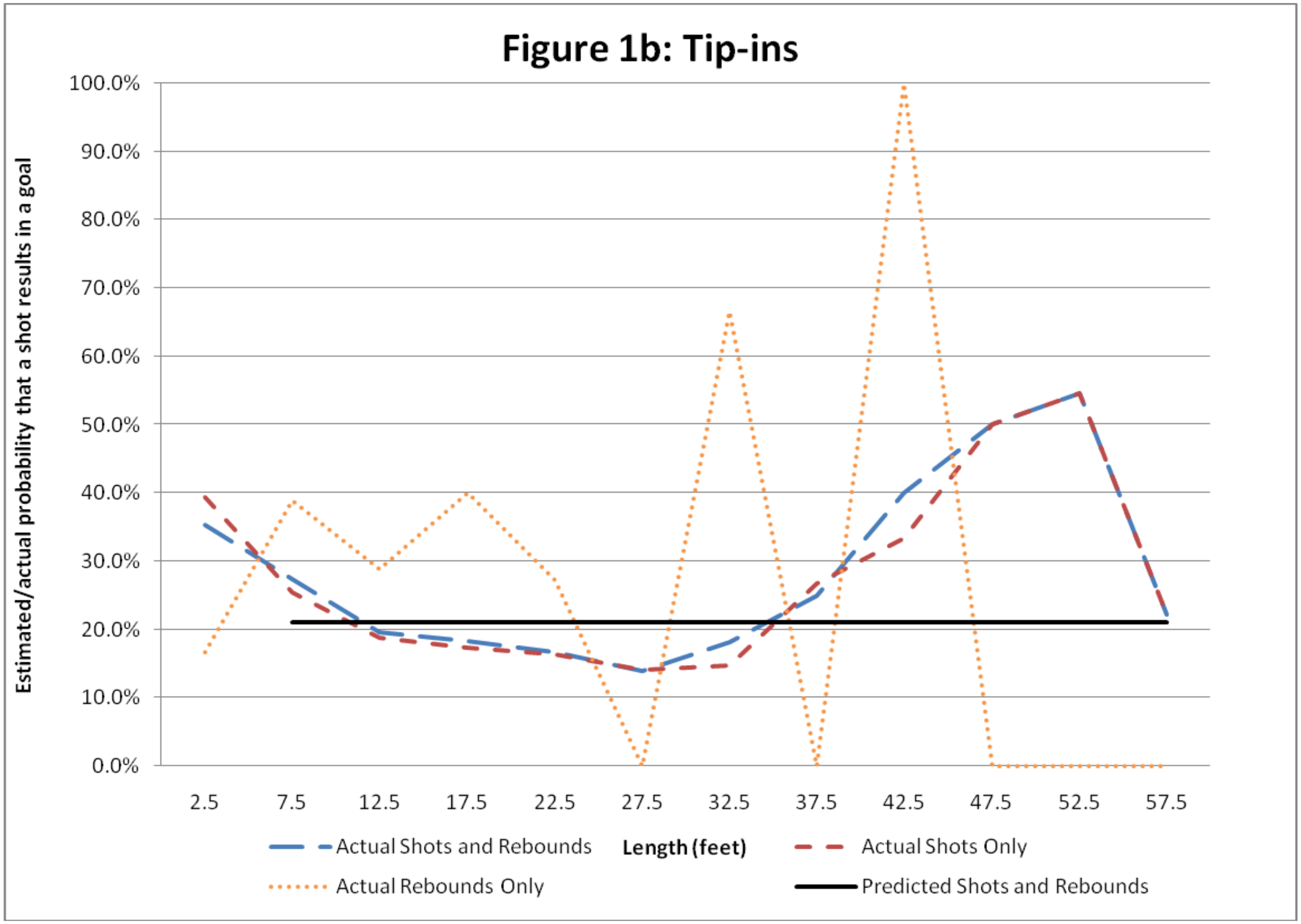


Figure 1b: Tip-ins
Estimated/actual probability that a shot results in a goal
100.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
2.5
7.5
12.5
17.5
22.5
27.5
32.5
37.5
42.5
47.5
52.5
57.5
Length (feet)
Actual Shots and Rebounds
Actual Shots Only
Actual Rebounds Only
Predicted Shots and Rebounds

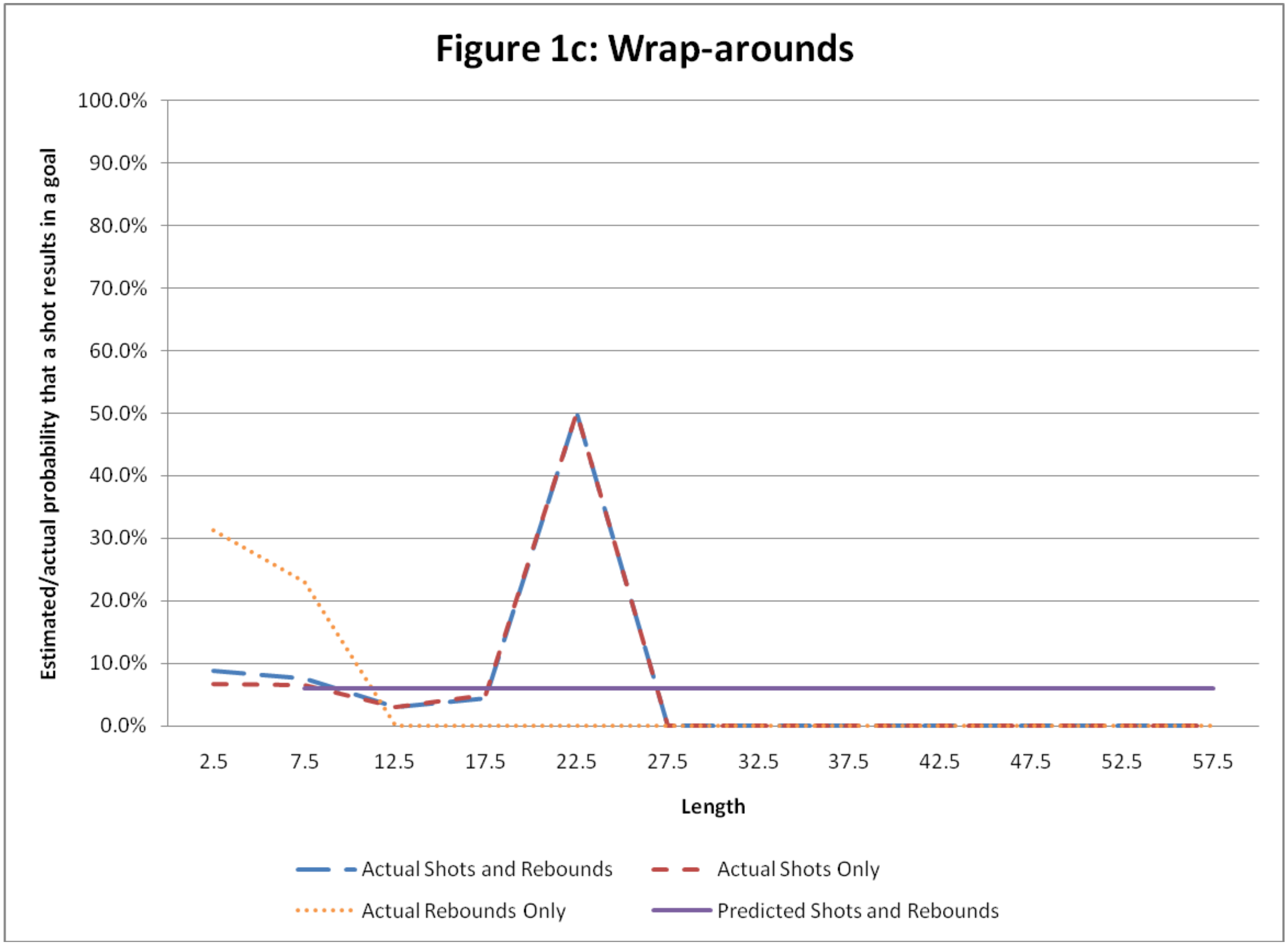


Figure 1c: Wrap-arounds

Figure 1d: Slaps

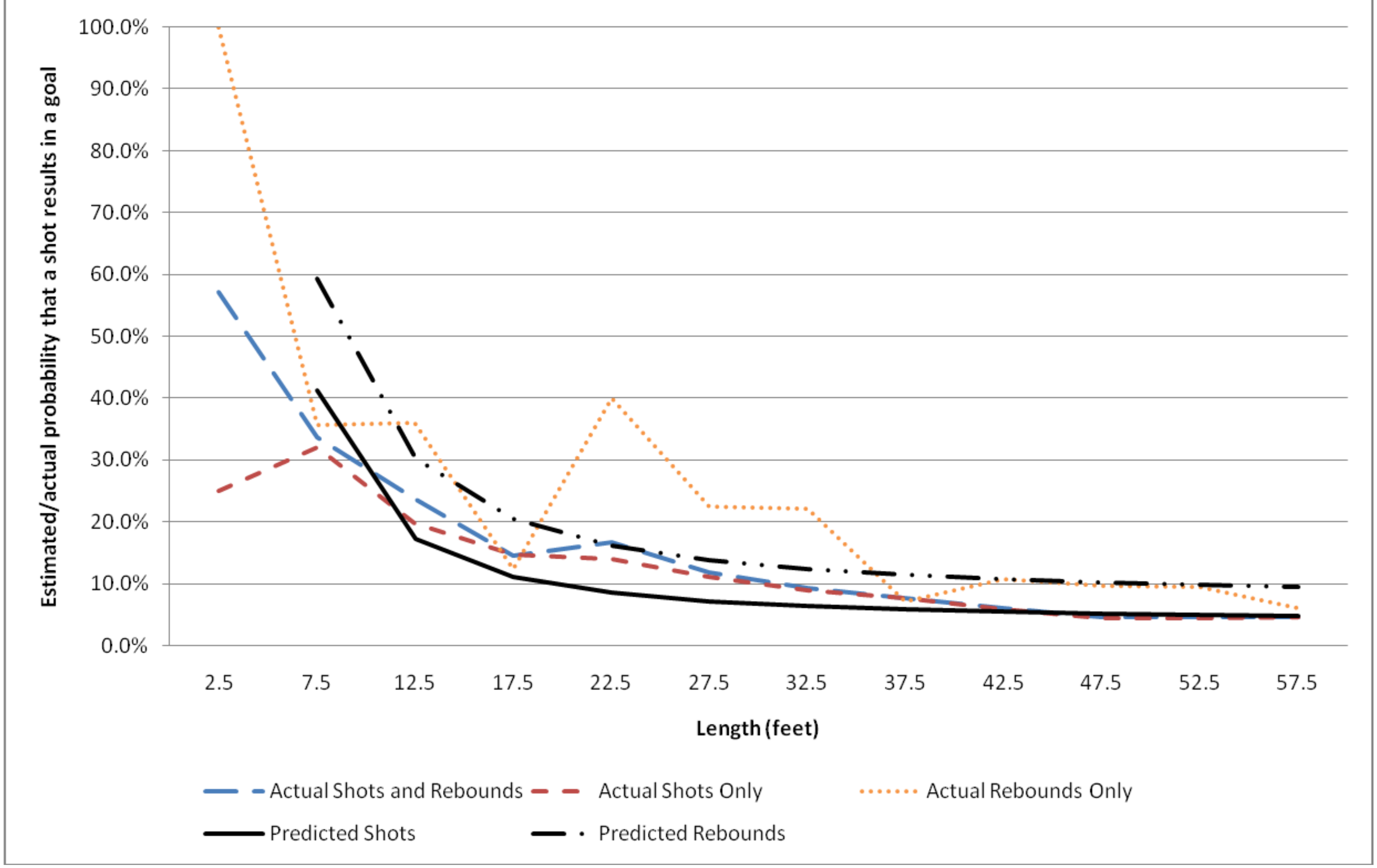
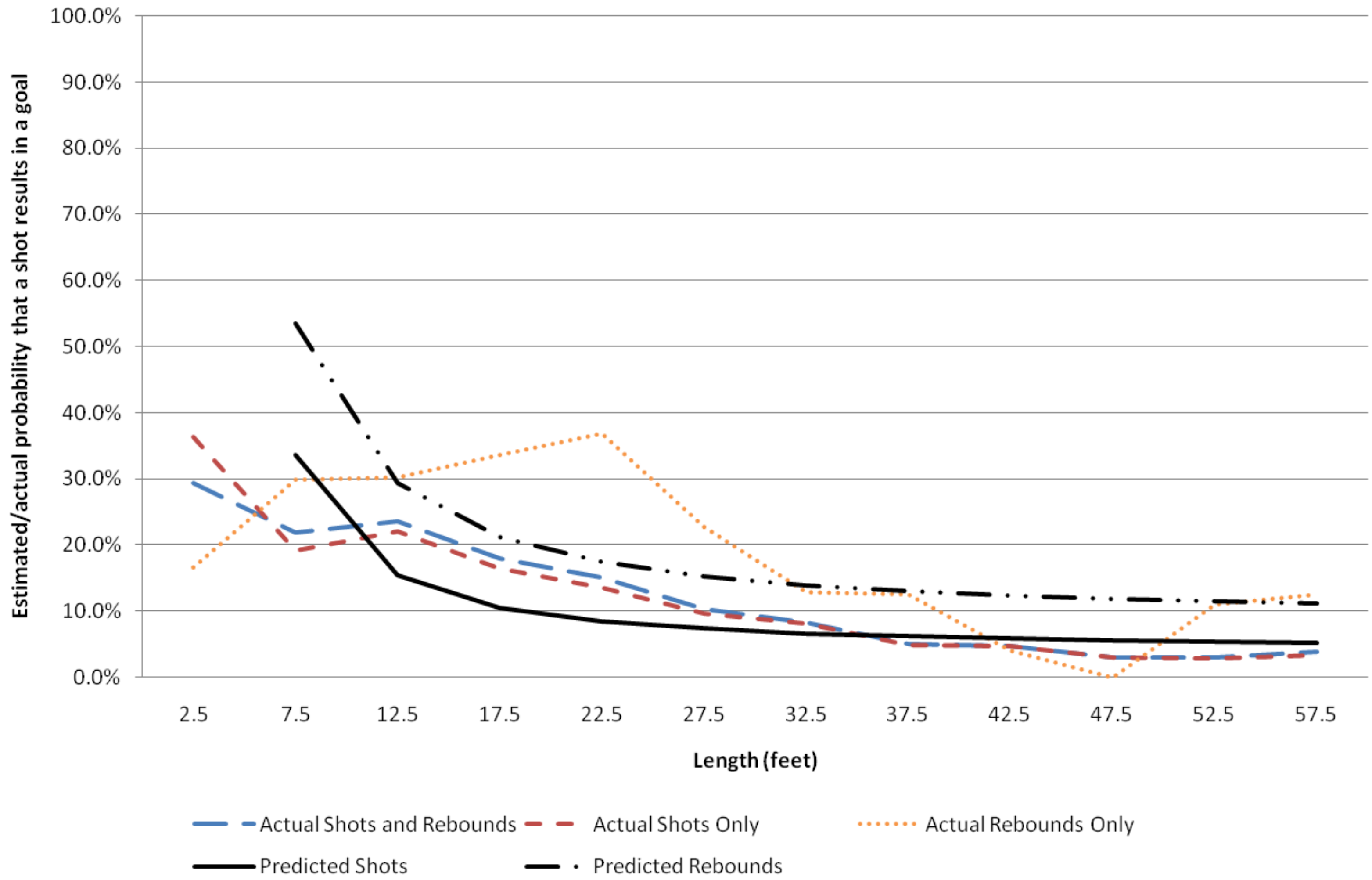


Figure 1e: Snaps



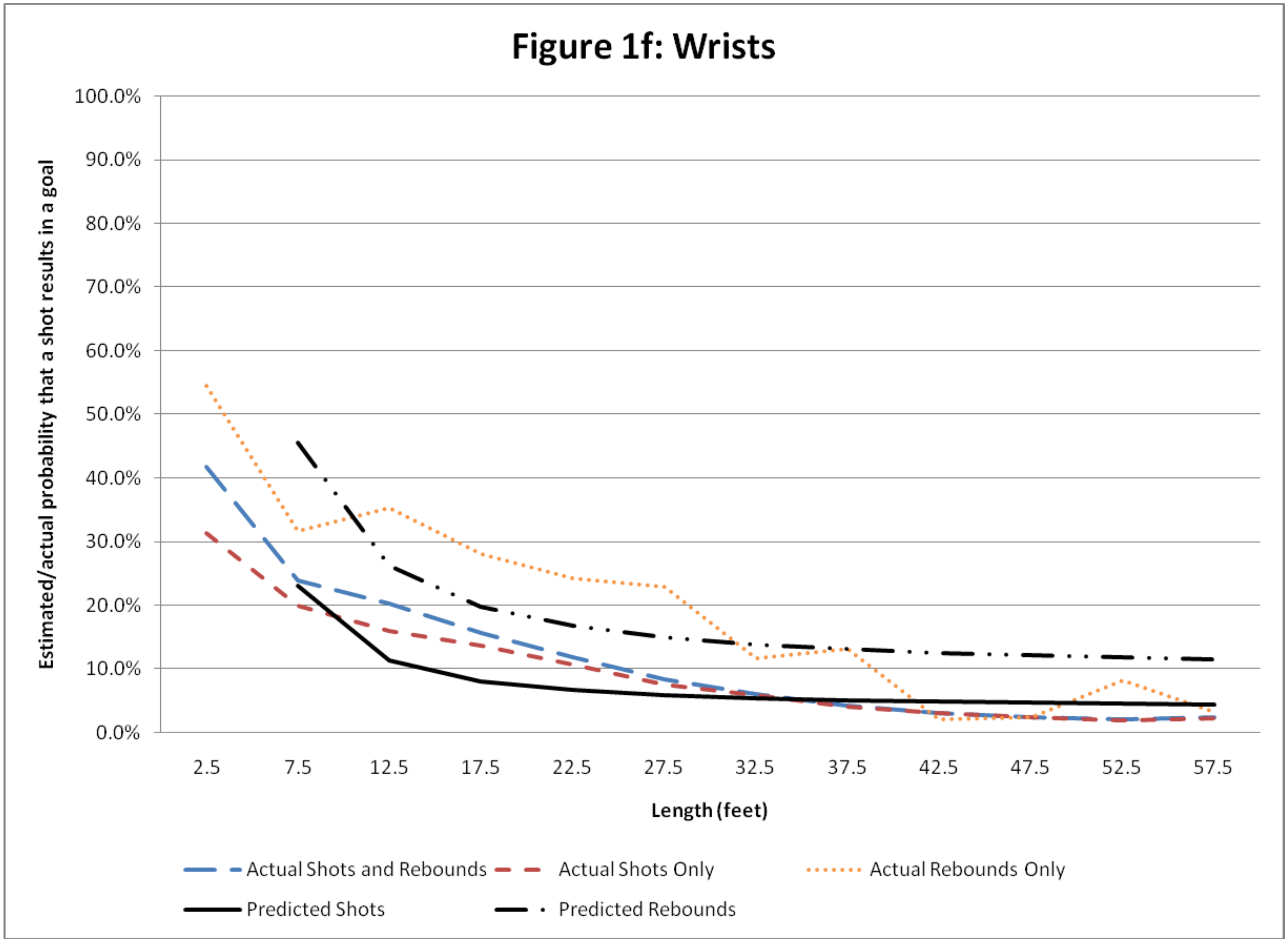


Figure 1f: Wrists
Estimated/actual probability that a shot results in a goal
100.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
2.5
7.5
12.5
17.5
22.5
27.5
32.5
37.5
42.5
47.5
52.5
57.5
Length (feet)
Actual Shots and Rebounds
Actual Shots Only
Actual Rebounds Only
Predicted Shots
Predicted Rebounds

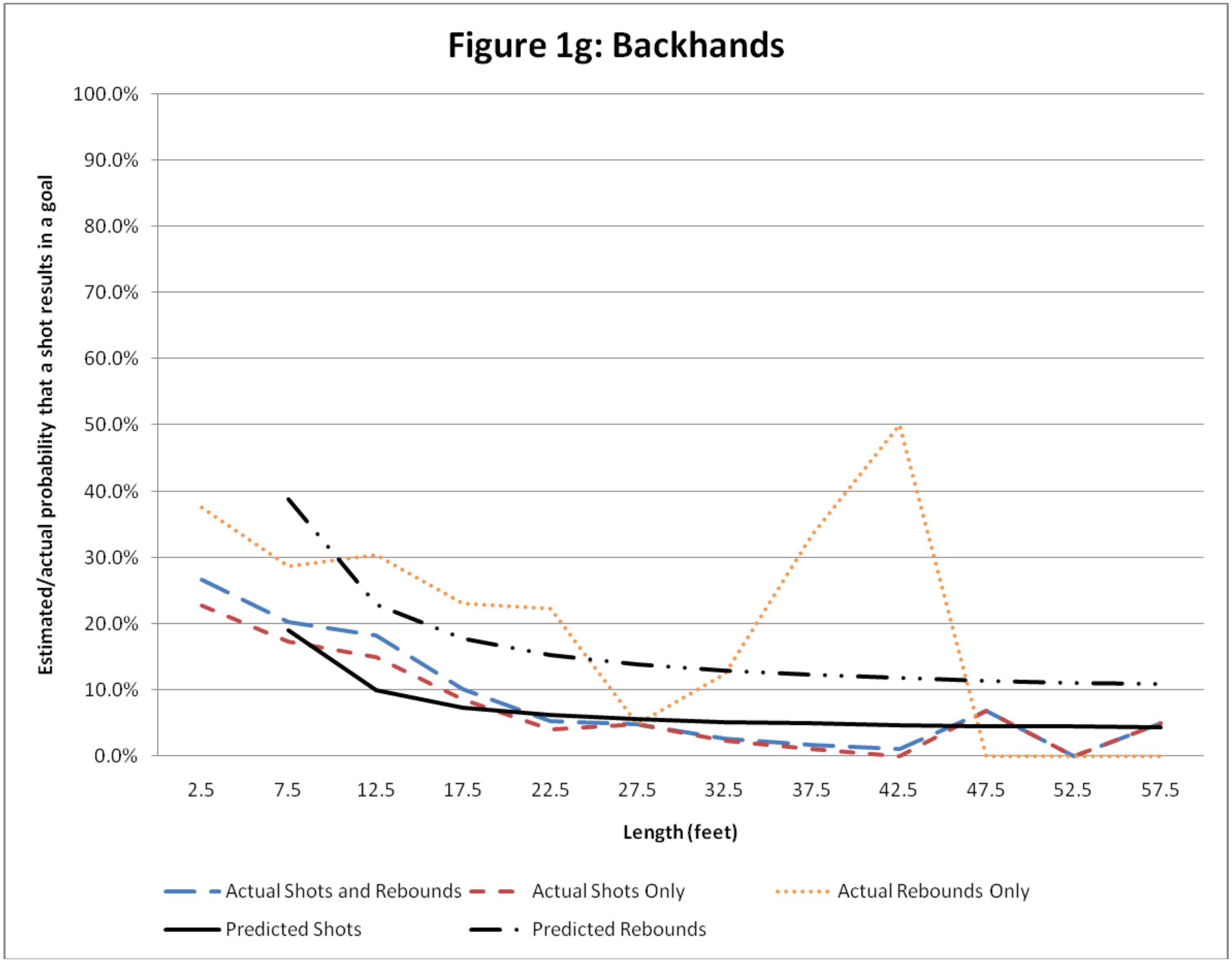


Figure 1g: Backhands
100.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
Estimated/actual probability that a shot results in a goal
2.5
7.5
12.5
17.5
22.5
27.5
32.5
37.5
42.5
47.5
52.5
57.5
Length (feet)
Actual Shots and Rebounds
Actual Shots Only
Actual Rebounds Only
Predicted Shots
Predicted Rebounds

Table 2. Logistic regression results in log-odds form of the probability that a shot results in a goal given shot characteristics.

Dependent variables	Coef.	Std. Err.	
Deflected	-2.329	(0.261)	***
Deflected * inverse length	11.386	(3.075)	***
Wrap-around	-2.637	(0.123)	***
Tip-ins	-1.262	(0.110)	***
Tip-ins * length	-0.013	(0.007)	*
Wrist	-3.222	(0.037)	***
Wrist * inverse length	15.361	(0.547)	***
Wrist * rebound	0.995	(0.050)	***
Slap	-3.471	(0.061)	***
Slap * inverse length	24.230	(1.777)	***
Slap * rebound	0.658	(0.139)	***
Snap	-3.145	(0.063)	***
Snap * inverse length	18.654	(1.195)	***
Snap * rebound	0.818	(0.107)	***
Backhand	-3.083	(0.100)	***
Backhand * inverse length	11.937	(1.120)	***
Backhand * rebound	0.980	(0.088)	***
Power-play	0.386	(0.031)	***
Short-handed	0.352	(0.074)	***

Note: ***, **, * indicates significance at the 1%, 5%, and 10% levels respectively.

Table 3. Summary of the predicted probability that each shot-type results in a goal for different shot lengths.

Shot Distance:	20 Feet	40 Feet	60 Feet	Mean*	
Shot-type		Traditional Shots			
Deflections	14.7%	11.5%	10.5%	16.7%	(15.7)
Wrap-arounds	6.7%	6.7%	6.7%	6.7%	(8.4)
Tip-ins	17.9%	14.3%	11.4%	18.8%	(15.3)
Wrists	7.9%	5.5%	4.9%	6.2%	(30.9)
Slaps	9.5%	5.4%	4.4%	5.0%	(46.2)
Snaps	9.9%	6.4%	5.6%	7.0%	(33.6)
Backhands	7.7%	5.8%	5.3%	8.1%	(18.4)
		Rebound Shots			
Deflections	14.7%	11.5%	10.5%	17.2%	(15.1)
Wrap-arounds	6.7%	6.7%	6.7%	6.7%	(7.8)
Tip-ins	17.9%	14.3%	11.4%	19.4%	(12.3)
Wrists	18.9%	13.7%	12.2%	21.3%	(16.7)
Slaps	16.8%	9.9%	8.2%	10.1%	(38.8)
Snaps	19.9%	13.5%	11.8%	18.4%	(22.3)
Backhands	18.1%	14.1%	13.0%	23.3%	(13.1)

*Note: Mean lengths in feet are the bracketed numbers.

Table 4. Logistic regression results in log-odds form and the marginal effects of the probability that a shot results in a goals given the shot quality, and player and goaltender characteristics.

	Logistic Regression			Marginal Effects		
Dependent Variables	Coef.	Std. Err.		Coef.	Std. Err.	
isgoalhat2008	6.253	(0.135)	***	0.493	(0.011)	***
5-9 goal scorer	0.704	(0.072)	***	0.068	(0.008)	***
10-14 goal scorer	0.883	(0.069)	***	0.089	(0.008)	***
15-19 goal scorer	1.027	(0.070)	***	0.110	(0.009)	***
20-24 goal scorer	1.112	(0.069)	***	0.123	(0.010)	***
25-29 goal scorer	1.197	(0.071)	***	0.140	(0.011)	***
30-34 goal scorer	1.248	(0.074)	***	0.151	(0.012)	***
35-39 goal scorer	1.277	(0.088)	***	0.162	(0.016)	***
40-44 goal scorer	1.335	(0.086)	***	0.173	(0.016)	***
45-49 goal scorer	1.404	(0.162)	***	0.191	(0.032)	***
50+ goal scorer	1.258	(0.147)	***	0.162	(0.027)	***
ANDERSON_CRAIG_2008	-4.088	(0.137)	***	-0.089	(0.001)	***
AULD_ALEX_2008	-3.934	(0.127)	***	-0.089	(0.001)	***
BACKSTROM_NIKLAS_2008	-4.009	(0.106)	***	-0.093	(0.001)	***
BIRON_MARTIN_2008	-4.040	(0.113)	***	-0.092	(0.001)	***
BISHOP_BEN_2008	-3.723	(0.313)	***	-0.085	(0.001)	***
BOUCHER_BRIAN_2008	-4.220	(0.184)	***	-0.087	(0.001)	***
BRODEUR_MARTIN_2008	-4.020	(0.138)	***	-0.088	(0.001)	***
BRYZGALOV_ILJA_2008	-3.757	(0.099)	***	-0.092	(0.001)	***
BUDAJ_PETER_2008	-3.742	(0.106)	***	-0.090	(0.001)	***
CLEMMENSEN_SCOTT_2008	-3.949	(0.124)	***	-0.089	(0.001)	***
CLIMIE_MATT_2008	-3.470	(0.327)	***	-0.084	(0.001)	***
CONKLIN_TY_2008	-4.021	(0.138)	***	-0.089	(0.001)	***
CURRY_JOHN_2008	-4.026	(0.430)	***	-0.085	(0.001)	***
DANIS_YANN_2008	-3.937	(0.137)	***	-0.088	(0.001)	***
DENIS_MARC_2008	-3.438	(1.193)	***	-0.083	(0.004)	***
DIPIETRO_RICK_2008	-3.801	(0.303)	***	-0.085	(0.001)	***
DROUINDESLAURIERS_JEFF_2008	-3.901	(0.219)	***	-0.086	(0.001)	***
DUBIELEWICZ_WADE_2008	-3.615	(0.377)	***	-0.084	(0.001)	***
ELLIOTT_BRIAN_2008	-3.766	(0.139)	***	-0.087	(0.001)	***
ELLIS_DAN_2008	-3.811	(0.128)	***	-0.088	(0.001)	***
ERSBERG_ERIK_2008	-3.729	(0.151)	***	-0.087	(0.001)	***
FERNANDEZ_MANNY_2008	-3.938	(0.148)	***	-0.088	(0.001)	***
FLEURY_MARCANDRE_2008	-3.953	(0.105)	***	-0.093	(0.001)	***
GARON_MATHIEU_2008	-3.811	(0.165)	***	-0.086	(0.001)	***
GERBER_MARTIN_2008	-3.806	(0.144)	***	-0.087	(0.001)	***
GIGUERE_JEANSEBASTIEN_2008	-3.776	(0.114)	***	-0.090	(0.001)	***
HALAK_JAROSLAV_2008	-4.045	(0.134)	***	-0.089	(0.001)	***

	Logistic Regression			Marginal Effects		
Dependent Variables	Coef.	Std. Err.		Coef.	Std. Err.	
HARDING_JOSH_2008	-4.189	(0.201)	***	-0.087	(0.001)	***
HEDBERG_JOHAN_2008	-3.705	(0.130)	***	-0.087	(0.001)	***
HILLER_JONAS_2008	-4.053	(0.123)	***	-0.090	(0.001)	***
HOWARD_JAMES_2008	-3.043	(0.554)	***	-0.082	(0.003)	***
HUET_CRISTOBAL_2008	-3.974	(0.126)	***	-0.089	(0.001)	***
JOHNSON_BRENT_2008	-3.820	(0.162)	***	-0.087	(0.001)	***
JOSEPH_CURTIS_2008	-3.531	(0.168)	***	-0.085	(0.001)	***
KHABIBULIN_NIKOLAI_2008	-4.055	(0.126)	***	-0.090	(0.001)	***
KIPRUSOFF_MIIKKA_2008	-3.886	(0.101)	***	-0.093	(0.001)	***
KOLZIG_OLAF_2008	-3.764	(0.231)	***	-0.085	(0.001)	***
KRAHN_BRENT_2008	-2.232	(0.774)	***	-0.076	(0.008)	***
LABARBERA_JASON_2008	-3.727	(0.140)	***	-0.087	(0.001)	***
LACOSTA_DANIEL_2008	-4.906	(0.686)	***	-0.086	(0.001)	***
LALIME_PATRICK_2008	-3.727	(0.145)	***	-0.087	(0.001)	***
LECLAIRE_PASCAL_2008	-3.418	(0.178)	***	-0.084	(0.001)	***
LEGACE_MANNY_2008	-3.538	(0.140)	***	-0.086	(0.001)	***
LEHTONEN_KARI_2008	-3.940	(0.110)	***	-0.091	(0.001)	***
LEIGHTON_MICHAEL_2008	-3.927	(0.172)	***	-0.087	(0.001)	***
LUNDQVIST_HENRIK_2008	-4.068	(0.105)	***	-0.094	(0.001)	***
LUONGO_ROBERTO_2008	-4.020	(0.112)	***	-0.091	(0.001)	***
MACDONALD_JOEY_2008	-3.859	(0.110)	***	-0.091	(0.001)	***
MANNINO_PETER_2008	-3.868	(0.375)	***	-0.085	(0.001)	***
MASON_STEVE_2008	-3.958	(0.105)	***	-0.092	(0.001)	***
MASON_CHRIS_2008	-3.959	(0.111)	***	-0.091	(0.001)	***
MCELHINNEY_CURTIS_2008	-3.610	(0.220)	***	-0.085	(0.001)	***
MCKENNA_MIKE_2008	-3.658	(0.175)	***	-0.085	(0.001)	***
MILLER_RYAN_2008	-3.991	(0.108)	***	-0.092	(0.001)	***
MONTOYA_AL_2008	-4.187	(0.441)	***	-0.085	(0.001)	***
NABOKOV_EVGENI_2008	-3.962	(0.112)	***	-0.092	(0.001)	***
NEUVIRTH_MICHAL_2008	-3.725	(0.356)	***	-0.084	(0.001)	***
NIEMI_ANTTI_2008	-3.569	(0.406)	***	-0.084	(0.002)	***
NIITTYMAKI_ANTERO_2008	-3.977	(0.137)	***	-0.089	(0.001)	***
NORRENA_FREDRIK_2008	-3.454	(0.255)	***	-0.084	(0.001)	***
OSGOOD_CHRIS_2008	-3.651	(0.114)	***	-0.088	(0.001)	***
PAVELEC_ONDREJ_2008	-3.607	(0.195)	***	-0.085	(0.001)	***
POGGE_JUSTIN_2008	-3.014	(0.211)	***	-0.082	(0.001)	***
PRICE_CAREY_2008	-3.851	(0.108)	***	-0.090	(0.001)	***
QUICK_JONATHAN_2008	-3.992	(0.124)	***	-0.090	(0.001)	***
RAMO_KARRI_2008	-3.617	(0.133)	***	-0.087	(0.001)	***
RAYCROFT_ANDREW_2008	-3.647	(0.131)	***	-0.087	(0.001)	***
RINNE_PEKKA_2008	-4.030	(0.117)	***	-0.091	(0.001)	***

	Logistic Regression			Marginal Effects		
Dependent Variables	Coef.	Std. Err.		Coef.	Std. Err.	
ROLOSON_DWAYNE_2008	-4.002	(0.107)	***	-0.093	(0.001)	***
SABOURIN_DANY_2008	-3.824	(0.167)	***	-0.086	(0.001)	***
SANFORD_CURTIS_2008	-3.875	(0.184)	***	-0.086	(0.001)	***
SCHNEIDER_CORY_2008	-3.406	(0.246)	***	-0.084	(0.001)	***
SMITH_MIKE_2008	-3.772	(0.114)	***	-0.089	(0.001)	***
STEPHAN_TOBIAS_2008	-3.433	(0.218)	***	-0.084	(0.001)	***
TELLQVIST_MIKAEL_2008	-3.867	(0.164)	***	-0.087	(0.001)	***
THEODORE_JOSE_2008	-3.742	(0.104)	***	-0.091	(0.001)	***
THOMAS_TIM_2008	-4.226	(0.118)	***	-0.092	(0.001)	***
TORDJMAN_JOSH_2008	-3.354	(0.476)	***	-0.083	(0.002)	***
TOSKALA_VESA_2008	-3.714	(0.106)	***	-0.090	(0.001)	***
TURCO_MARTY_2008	-3.790	(0.098)	***	-0.093	(0.001)	***
VARLAMOV_SIMEON_2008	-4.090	(0.336)	***	-0.085	(0.001)	***
VOKOUN_TOMAS_2008	-4.093	(0.108)	***	-0.093	(0.001)	***
WARD_CAM_2008	-4.092	(0.109)	***	-0.093	(0.001)	***
WEEKES_KEVIN_2008	-3.951	(0.201)	***	-0.086	(0.001)	***

Note: ***, **, * indicates significance at the 1%, 5%, and 10% levels respectively.

Note: Marginal effect of isgoalhatstage1 is taken at the mean=0.104.

Table 5. Summary statistics of isgoalhat and the player characteristics

Variable	Mean	Std. Dev.	Min	Max
isgoalhatstage1	0.104	0.081	0.045	0.918
0-4 goal scorer	0.126	0.332	0.000	1.000
5-9 goal scorer	0.152	0.359	0.000	1.000
10-14 goal scorer	0.176	0.381	0.000	1.000
15-19 goal scorer	0.143	0.350	0.000	1.000
20-24 goal scorer	0.138	0.345	0.000	1.000
25-29 goal scorer	0.103	0.304	0.000	1.000
30-34 goal scorer	0.080	0.272	0.000	1.000
35-39 goal scorer	0.034	0.182	0.000	1.000
40-44 goal scorer	0.035	0.183	0.000	1.000
45-49 goal scorer	0.005	0.073	0.000	1.000
50+ goal scorer	0.008	0.091	0.000	1.000

Figure 3: Predicted probability that a shot results in a goal for each group of goal scorers for different levels of shot qualities against the average goaltender.

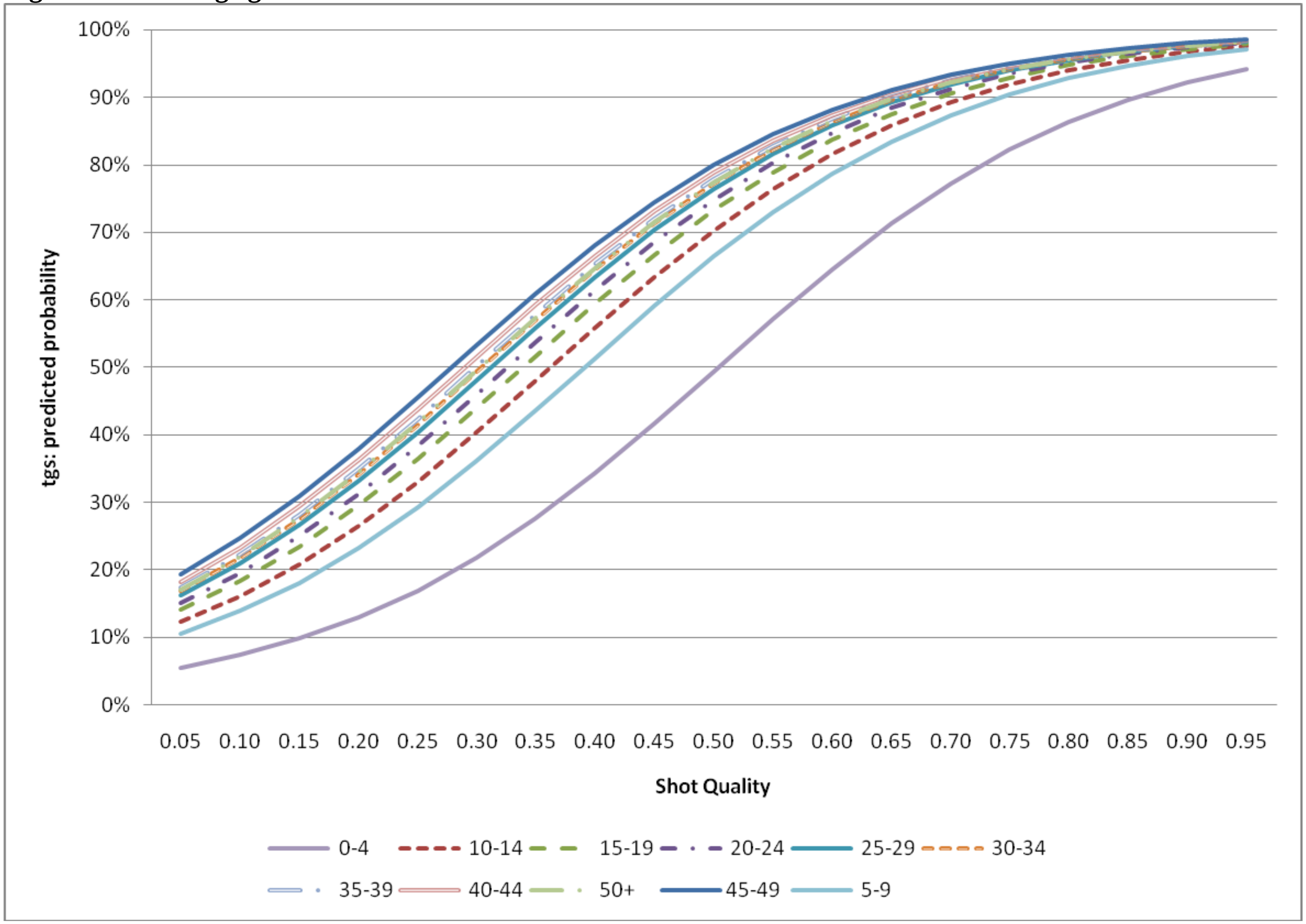


Figure 4: Predicted probability that a shot results in a goal for goaltenders Tim Thomas and Jose Theodore against a 10-14 goal scorer.

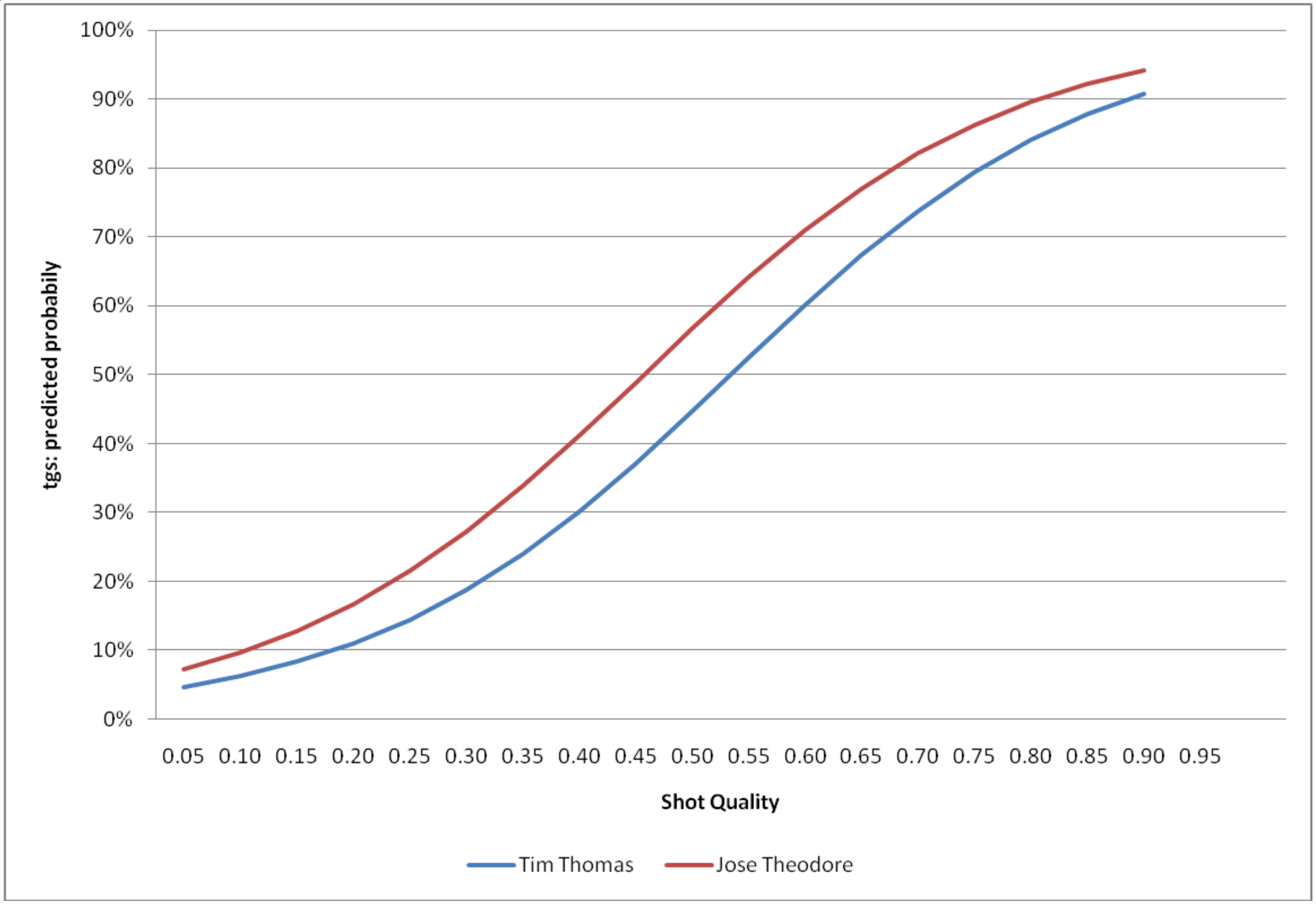


Figure 5: Histogram of Theoretical Goals Scored: The predicted probability that a shot results in a goal given shot quality, and player and goaltender characteristics.

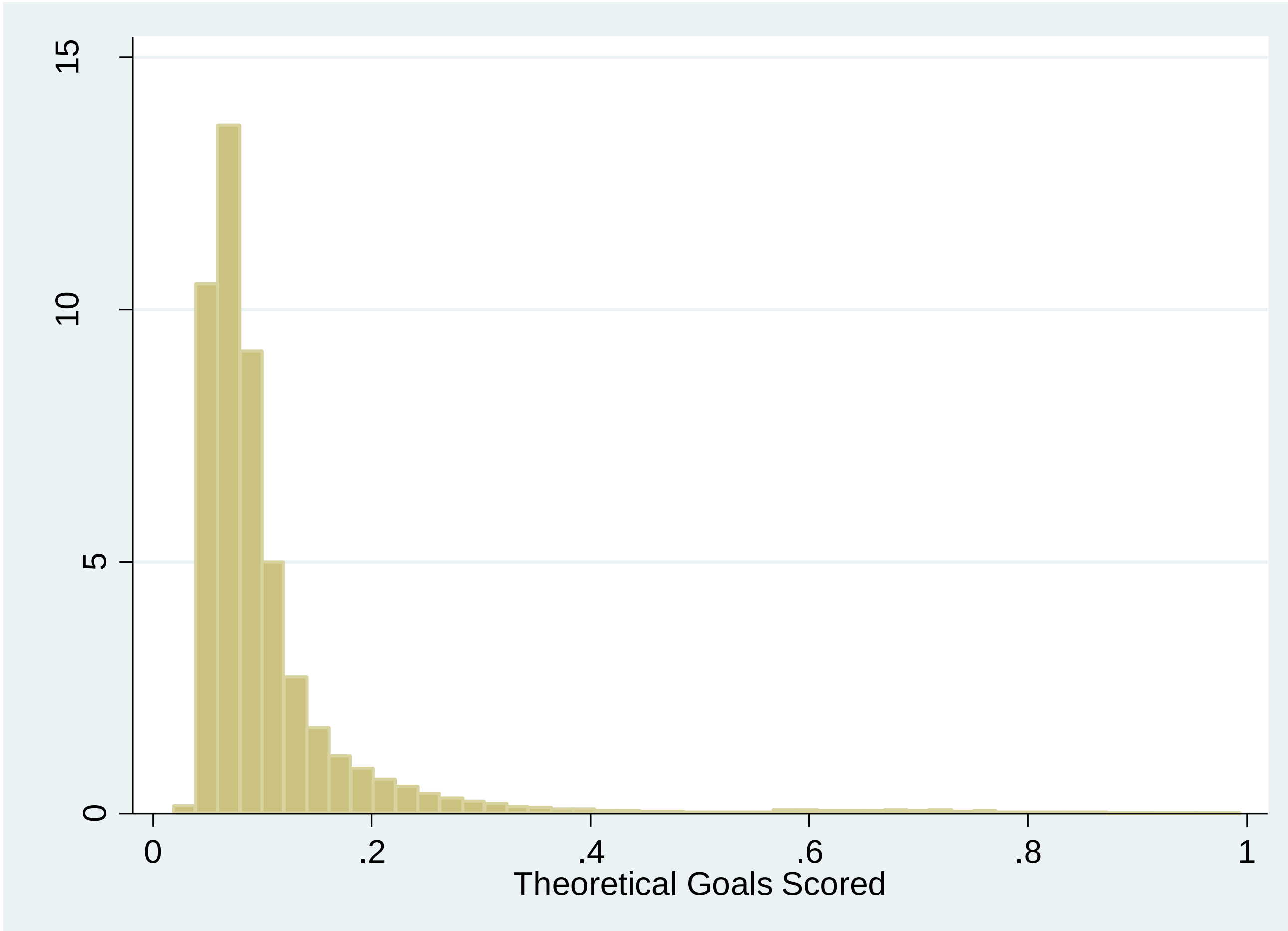


Table 6. Summary statistics of TGS and team 1 home game.

	Mean	Std. Dev.	Min	Max
Team 1 TGS	3.180	1.137	0.870	10.417
Team 2 TGS	3.158	1.021	0.933	7.391
Team 1 home game	0.500	0.500	0.000	1.000

Table 7. Logistic regression results in log-odds form and their marginal effects of the probability of win given each teams' TGS and home-ice advantage.

	Regression Results			Marginal Effects		
	Coef.	Std. Err.		Coef.	Std. Err.	
			Difference Form of CSF			
Dependent variables						
Difference TGS	0.314	(0.034)	***	0.079	(0.008)	***
Home	0.323	(0.092)	***	0.081	(0.023)	***
Constant	-0.161	(0.064)	**			
			Ratio Form of CSF			
Ratio TGS	1.027	(0.099)	***	0.086	(0.025)	***
Home	0.322	(0.092)	***	0.080	(0.023)	***
Constant	-0.161	(0.064)	**			

Note: ***, **, * indicates significance at the 1%, 5%, and 10% levels respectively.
The marginal effects are taken at TGS 1 = TGS 2

Figure 6: Graphs of the CSFs with the effect of home-ice advantage removed: the probability of a win for values of TGS_1 holding TGS_2 constant at 3.00.

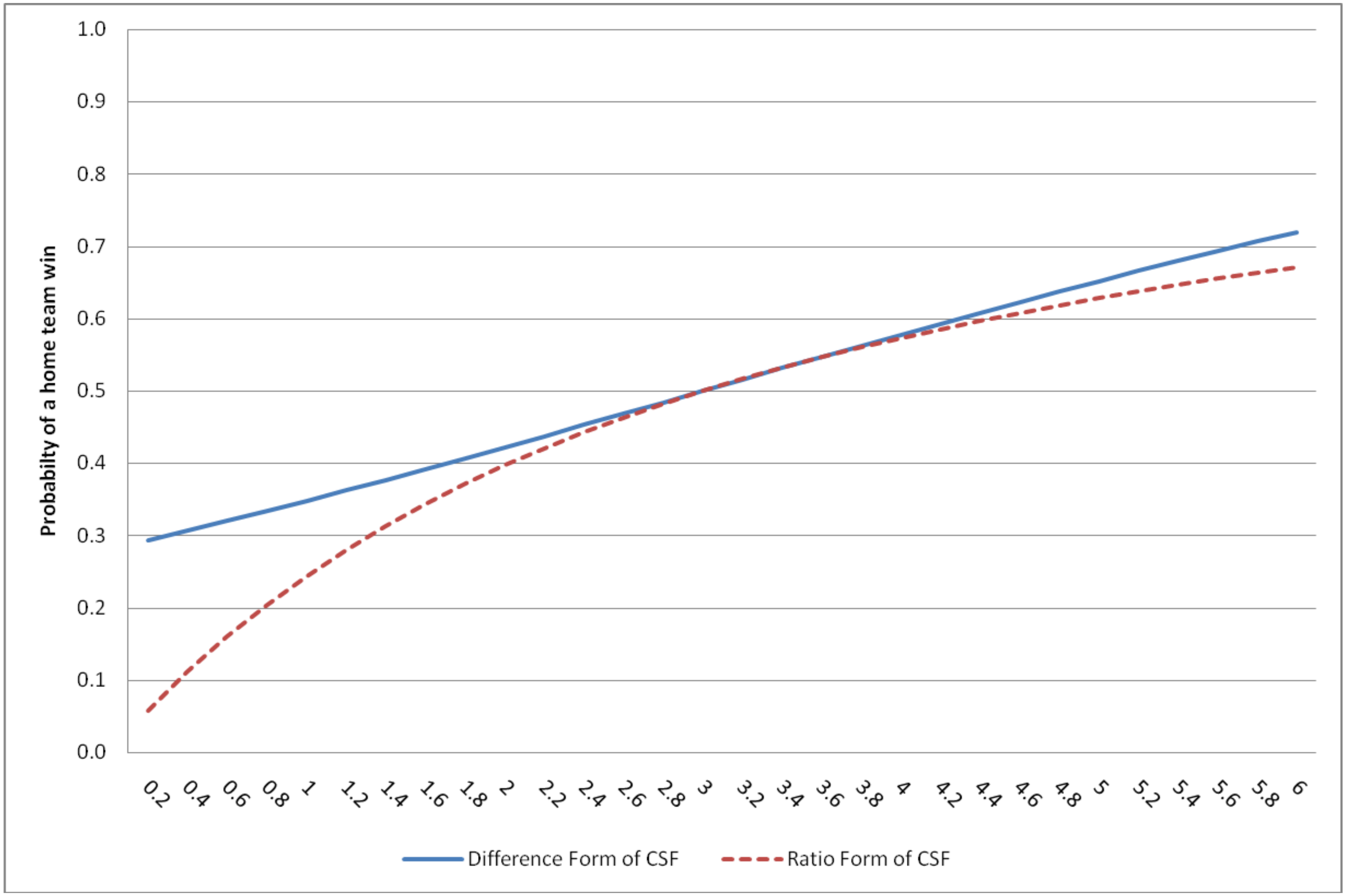


Figure 7: Marginal probability of winning of TGS_1 holding TGS_2 constant at 3.00. The marginal effects are calculated with the effects of home-ice advantage removed.

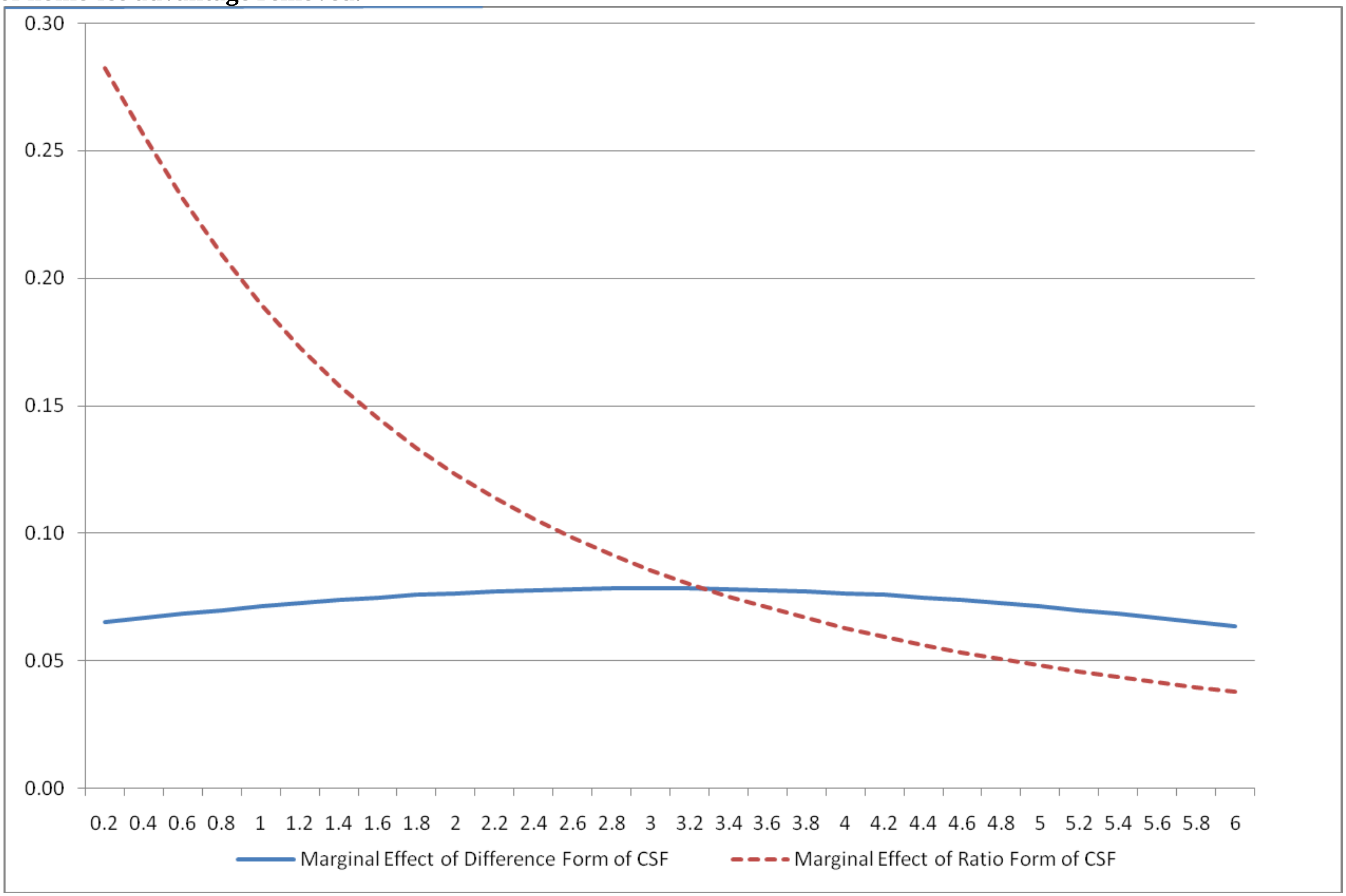


Table 8. In-sample classification tables based.

	Difference Form			Ratio Form		
	Observed			Observed		
Classified	Win	Lose	Total	Win	Lose	Total
Win	339	186	525	339	187	526
Lose	216	321	537	216	320	536
Total	555	507	1062	555	507	1062

Classification Metrics	Diff Form	Ratio Form
Sensitivity:(class wins & obs wins/total obs wins)%	61.1%	61.1%
Specificity: (class losses & obs losses/total obs losses)%	63.3%	63.1%
Positive predictive value: (class wins & obs wins/total class wins)%	64.6%	64.4%
Negative predictive value: (class losses & obs losses/total class losses)%	59.8%	59.7%
Correctly classified: ((class wins & obs wins + class losses & obs losses)/total)%	62.1%	62.1%

Table 9. Out-of-sample classification tables.

	Difference Form			Ratio Form		
	Observed			Observed		
Classified	Win	Lose	Total	Win	Lose	Total
Win	93	40	133	95	39	134
Lose	52	77	129	50	78	128
Total	145	117	262	145	117	262

Classification Metrics	Diff Form	Ratio Form
Sensitivity:(class wins & obs wins/total obs wins)%	64.1%	65.5%
Specificity: (class losses & obs losses/total obs losses)%	65.8%	66.7%
Positive predictive value: (class wins & obs wins/total class wins)%	69.9%	70.9%
Negative predictive value: (class losses & obs losses/total class losses)%	59.7%	60.9%
Correctly classified: ((class wins & obs wins + class losses & obs losses)/total)%	64.9%	66.0%

Note: Out of sample properties are derived by re-estimating the coefficients with the first 1600 observations and predicted on the final 262 observations.

Table 10. In-sample Hosmer-Lemeshow tables and test statistic calculation

Difference Form							Ratio Form						
Group	Prob	Obs win	Exp win	Obs loss	Exp loss	Total	Group	Prob	Obs win	Exp win	Obs loss	Exp loss	Total
1	0.3337	30	29.9	77	77.1	107	1	0.318	31	28.7	76	78.3	107
2	0.3869	41	38.1	65	67.9	106	2	0.3761	43	37.2	63	68.8	106
3	0.4337	45	43.5	61	62.5	106	3	0.4241	40	42.7	66	63.3	106
4	0.4644	48	47.6	58	58.4	106	4	0.4619	54	47.1	52	58.9	106
5	0.4977	49	51.1	57	54.9	106	5	0.4979	45	50.9	61	55.1	106
6	0.5349	59	55.2	48	51.8	107	6	0.5356	62	55.2	45	51.8	107
7	0.5709	64	58.7	42	47.3	106	7	0.5722	61	58.8	45	47.2	106
8	0.6156	66	63	40	43	106	8	0.6183	66	63.3	40	42.7	106
9	0.668	75	67.7	31	38.3	106	9	0.6756	79	68.2	27	37.8	106
10	0.9333	78	77.5	28	28.5	106	10	0.8914	74	77.9	32	28.1	106
number of observations = 1062							number of observations = 1062						
number of groups = 10							number of groups = 10						
Hosmer-Lemeshow chi2(8) = 4.78							Hosmer-Lemeshow chi2(8) = 12.75						
Prob > chi2 = 0.7806							Prob > chi2 = 0.1207						

Table 11. Out-of-sample Hosmer-Lemeshow tables and test statistic calculation

Difference Form							Ratio Form						
Group	Prob	Obs win	Exp win	Obs loss	Exp loss	Total	Group	Prob	Obs win	Exp win	Obs loss	Exp loss	Total
1	0.3269	9	7.6	18	19.4	27	1	0.3073	7	7.2	20	19.8	27
2	0.3796	7	9.2	19	16.8	26	2	0.3638	9	8.9	17	17.1	26
3	0.4339	12	10.5	14	15.5	26	3	0.4218	13	10.3	13	15.7	26
4	0.4681	15	11.7	11	14.3	26	4	0.4595	14	11.5	12	14.5	26
5	0.5024	11	12.5	15	13.5	26	5	0.5031	10	12.5	16	13.5	26
6	0.5432	16	14	11	13	27	6	0.5464	16	14.1	11	12.9	27
7	0.5832	16	14.6	10	11.4	26	7	0.5771	16	14.6	10	11.4	26
8	0.6206	19	15.7	7	10.3	26	8	0.6233	22	15.7	4	10.3	26
9	0.6508	21	16.4	5	9.6	26	9	0.6672	19	16.6	7	9.4	26
10	0.8673	19	18.6	7	7.4	26	10	0.8807	19	18.8	7	7.2	26
number of observations = 280							number of observations = 280						
number of groups = 10							number of groups = 10						
Hosmer-Lemeshow chi2(8) = 9.74							Hosmer-Lemeshow chi2(8) = 11.35						
Prob > chi2 = 0.2841							Prob > chi2 = 0.1826						

Table 12: McFadden's LRI, AIC and BIC.

Model	Ratio Form	Difference Form	Difference
McFadden's LRI	0.055	0.051	0.004
AIC	1.313	1.319	-0.005
BIC	-13465.269	-13454.441	-10.828

Table 13. Logistic regression results in log-odds form and the marginal effects of the probability that a shot results in a goals given the shot quality, other player, other goaltender, and Team Canada candidate players and goaltender characteristics.

		Logistic Regression			Marginal Effects		
Variable Type	Variable	Coef.	Std. Err.		Coef.	Std. Err.	
2008 shot quality	2008 isgoalhat	6.261	(0.135)	***	0.789	(0.011)	***
2009 shot quality	2009 isgoalhat	5.799	(0.176)	***	0.731	(0.014)	***
2008 Other PC	2008 5-9 goal scorer	0.696	(0.074)	***	0.106	(0.009)	***
2009 Other PC	5-9 goal scorer	0.870	(0.104)	***	0.141	(0.015)	***
2008 Other PC	2008 10-14 goal scorer	0.898	(0.071)	***	0.143	(0.009)	***
2009 Other PC	2009 10-14 goal scorer	1.183	(0.103)	***	0.209	(0.017)	***
2008 Other PC	2008 15-19 goal scorer	1.017	(0.071)	***	0.168	(0.010)	***
2009 Other PC	2009 15-19 goal scorer	1.204	(0.098)	***	0.210	(0.016)	***
2008 Other PC	2008 20-24 goal scorer	1.103	(0.071)	***	0.186	(0.011)	***
2009 Other PC	2009 20-24 goal scorer	1.361	(0.100)	***	0.249	(0.018)	***
2008 Other PC	2008 25-29 goal scorer	1.218	(0.074)	***	0.214	(0.012)	***
2009 Other PC	2009 25-29 goal scorer	1.405	(0.105)	***	0.262	(0.020)	***
2008 Other PC	2008 30-34 goal scorer	1.266	(0.080)	***	0.228	(0.014)	***
2009 Other PC	2009 30-34 goal scorer	1.479	(0.111)	***	0.281	(0.022)	***
2008 Other PC	2008 35-39 goal scorer	1.394	(0.108)	***	0.262	(0.021)	***
2009 Other PC	2009 35-39 goal scorer	1.575	(0.141)	***	0.307	(0.030)	***
2008 Other PC	2008 40-44 goal scorer	1.356	(0.093)	***	0.252	(0.017)	***
2009 Other PC	2009 40-44 goal scorer	1.735	(0.176)	***	0.347	(0.040)	***
2008 Other PC	2008 45-49 goal scorer	2.234	(0.374)	***	0.470	(0.093)	***
2008 Other PC	2008 50+ goal scorer	1.255	(0.148)	***	0.230	(0.027)	***
2009 Other PC	2009 50+ goal scorer	1.788	(0.162)	***	0.360	(0.037)	***
2008 TCC PC	BEAUCHEMIN_FRANCIOS_2008	12.400	(0.996)	***	0.168	(0.105)	
2008 TCC PC	BERGERON_PATRICE_2008	11.661	(0.852)	***	0.016	(0.035)	
2008 TCC PC	BOUWMEESTER_JAY_2008	12.568	(0.803)	***	0.179	(0.049)	**
2008 TCC PC	BOYLE_DAN_2008	12.370	(0.790)	***	0.162	(0.041)	***
2008 TCC PC	BURNS_BRENT_2008	12.234	(0.831)	***	0.110	(0.049)	
2008 TCC PC	CARTER_JEFF_2008	11.490	(0.673)	***	0.238	(0.033)	***

Variable Type	Variable	Logistic Regression Coef.	Logistic Regression Std. Err.		Marginal Effects Coef.	Marginal Effects Std. Err.	
2008 TCC PC	CLEARY_DANIEL_2008	12.065	(0.807)	***	0.079	(0.036)	
2008 TCC PC	CROSBY_SIDNEY_2008	12.230	(0.770)	***	0.214	(0.037)	***
2008 TCC PC	DOAN_SHANE_2008	12.444	(0.775)	***	0.234	(0.040)	***
2008 TCC PC	DOUGHTY_DREW_2008	12.538	(0.844)	***	0.130	(0.056)	
2008 TCC PC	GAGNE_SIMON_2008	12.167	(0.773)	***	0.200	(0.038)	***
2008 TCC PC	GETZLAF_RYAN_2008	12.354	(0.773)	***	0.202	(0.036)	***
2008 TCC PC	GREEN_MIKE_2008	12.548	(0.774)	***	0.291	(0.046)	***
2008 TCC PC	HAMHUIS_DAN_2008	12.405	(0.992)	***	-0.004	(0.045)	
2008 TCC PC	HEATLEY_DANY_2008	12.328	(0.769)	***	0.237	(0.039)	***
2008 TCC PC	IGINLA_JAROME_2008	12.273	(0.772)	***	0.195	(0.035)	***
2008 TCC PC	KEITH_DUNCAN_2008	12.492	(0.839)	***	0.121	(0.053)	
2008 TCC PC	LECAVALIER_VINCENT_2008	12.277	(0.772)	***	0.196	(0.035)	***
2008 TCC PC	LUCIC_MILAN_2008	12.982	(0.795)	***	0.305	(0.059)	***
2008 TCC PC	MARLEAU_PATRICK_2008	12.239	(0.770)	***	0.208	(0.035)	***
2008 TCC PC	MCDONALD_ANDY_2008	12.473	(0.793)	***	0.230	(0.050)	***
2008 TCC PC	MORROW_BRENDEN_2008	11.930	(0.874)	***	0.092	(0.056)	
2008 TCC PC	NASH_RICK_2008	12.404	(0.767)	***	0.246	(0.037)	***
2008 TCC PC	NIEDERMAYER_SCOTT_2008	12.400	(0.798)	***	0.143	(0.042)	**
2008 TCC PC	PERRY_COREY_2008	12.218	(0.769)	***	0.183	(0.032)	***
2008 TCC PC	PHANEUF_DION_2008	11.921	(0.818)	***	0.055	(0.036)	
2008 TCC PC	PRONGER_CHRIS_2008	12.406	(0.814)	***	0.144	(0.048)	**
2008 TCC PC	RICHARDS_MIKE_2008	12.342	(0.775)	***	0.211	(0.038)	***
2008 TCC PC	ROBIDAS_STEPHANE_2008	12.429	(0.953)	***	-0.001	(0.040)	
2008 TCC PC	ROY_DEREK_2008	12.284	(0.777)	***	0.187	(0.037)	***
2008 TCC PC	SEABROOK_BRENT_2008	12.584	(0.845)	***	0.140	(0.058)	
2008 TCC PC	SHARP_PATRICK_2008	12.419	(0.783)	***	0.229	(0.045)	***
2008 TCC PC	SPEZZA_JASON2008	11.907	(0.778)	***	0.109	(0.030)	**
2008 TCC PC	SMYTH_RYAN_2008	12.468	(0.773)	***	0.240	(0.039)	***
2008 TCC PC	STLOUIS_MARTIN_2008	12.399	(0.775)	***	0.213	(0.038)	***
2008 TCC PC	STAAL_ERIC_2008	11.916	(0.767)	***	0.146	(0.029)	***

Variable Type	Variable	Logistic Regression			Marginal Effects		
		Coef.	Std. Err.		Coef.	Std. Err.	
2008 TCC PC	STAAL_JORDAN_2008	12.507	(0.788)	***	0.211	(0.045)	***
2008 TCC PC	STAAL_MARC_2008	12.538	(0.981)	***	0.013	(0.048)	
2008 TCC PC	THORNTON_JOE_2008	12.780	(0.782)	***	0.276	(0.048)	***
2008 TCC PC	TOEWS_JONATHAN_2008	12.590	(0.773)	***	0.270	(0.042)	***
2008 TCC PC	WEBER_SHEA_2008	12.415	(0.787)	***	0.190	(0.043)	***
2008 Other GC	ANDERSON_CRAIG_2008	-4.085	(0.138)	***	-0.149	(0.001)	***
2008 Other GC	AULD_ALEX_2008	-3.929	(0.128)	***	-0.150	(0.001)	***
2008 Other GC	BACKSTROM_NIKLAS_2008	-4.002	(0.107)	***	-0.154	(0.001)	***
2008 Other GC	BIRON_MARTIN_2008	-4.037	(0.113)	***	-0.153	(0.001)	***
2008 Other GC	BISHOP_BEN_2008	-3.729	(0.313)	***	-0.144	(0.001)	***
2008 Other GC	BOUCHER_BRIAN_2008	-4.223	(0.185)	***	-0.148	(0.001)	***
TCC 2008 GC	BRODEUR_MARTIN_2008	-4.010	(0.138)	***	-0.149	(0.001)	***
2008 Other GC	BRYZGALOV_ILJA_2008	-3.756	(0.100)	***	-0.152	(0.001)	***
2008 Other GC	BUDAJ_PETER_2008	-3.741	(0.107)	***	-0.150	(0.001)	***
2008 Other GC	CLEMMENSEN_SCOTT_2008	-3.950	(0.125)	***	-0.150	(0.001)	***
2008 Other GC	CLIMIE_MATT_2008	-3.480	(0.327)	***	-0.143	(0.001)	***
2008 Other GC	CONKLIN_TY_2008	-4.022	(0.139)	***	-0.149	(0.001)	***
2008 Other GC	CURRY_JOHN_2008	-4.022	(0.430)	***	-0.145	(0.001)	***
2008 Other GC	DANIS_YANN_2008	-3.928	(0.138)	***	-0.148	(0.001)	***
2008 Other GC	DENIS_MARC_2008	-3.449	(1.189)	***	-0.142	(0.004)	***
2008 Other GC	DIPIETRO_RICK_2008	-3.788	(0.302)	***	-0.145	(0.001)	***
2008 Other GC	DROUINDESLAURIERS_JEFF_2008	-3.892	(0.219)	***	-0.146	(0.001)	***
2008 Other GC	DUBIELEWICZ_WADE_2008	-3.627	(0.377)	***	-0.144	(0.001)	***
2008 Other GC	ELLIOTT_BRIAN_2008	-3.764	(0.139)	***	-0.147	(0.001)	***
2008 Other GC	ELLIS_DAN_2008	-3.806	(0.129)	***	-0.148	(0.001)	***
2008 Other GC	ERSBERG_ERIK_2008	-3.722	(0.152)	***	-0.147	(0.001)	***
2008 Other GC	FERNANDEZ_MANNY_2008	-3.934	(0.149)	***	-0.148	(0.001)	***
TCC 2008 GC	FLEURY_MARCANDRE_2008	-3.954	(0.106)	***	-0.153	(0.001)	***
2008 Other GC	GARON_MATHIEU_2008	-3.801	(0.166)	***	-0.146	(0.001)	***
2008 Other GC	GERBER_MARTIN_2008	-3.807	(0.144)	***	-0.147	(0.001)	***

Variable Type	Variable	Logistic Regression Coef.	Logistic Regression Std. Err.		Marginal Effects Coef.	Marginal Effects Std. Err.	
2008 Other GC	GIGUERE_JEANSEBASTIEN_2008	-3.772	(0.115)	***	-0.149	(0.001)	***
2008 Other GC	HALAK_JAROSLAV_2008	-4.038	(0.135)	***	-0.150	(0.001)	***
2008 Other GC	HARDING_JOSH_2008	-4.189	(0.202)	***	-0.147	(0.001)	***
2008 Other GC	HEDBERG_JOHAN_2008	-3.705	(0.130)	***	-0.147	(0.001)	***
2008 Other GC	HILLER_JONAS_2008	-4.052	(0.123)	***	-0.151	(0.001)	***
2008 Other GC	HOWARD_JAMES_2008	-3.038	(0.555)	***	-0.140	(0.003)	***
2008 Other GC	HUET_CRISTOBAL_2008	-3.975	(0.126)	***	-0.150	(0.001)	***
2008 Other GC	JOHNSON_BRENT_2008	-3.818	(0.162)	***	-0.147	(0.001)	***
2008 Other GC	JOSEPH_CURTIS_2008	-3.517	(0.168)	***	-0.144	(0.001)	***
2008 Other GC	KHABIBULIN_NIKOLAI_2008	-4.051	(0.127)	***	-0.150	(0.001)	***
2008 Other GC	KIPRUSOFF_MIIKKA_2008	-3.886	(0.102)	***	-0.154	(0.001)	***
2008 Other GC	KOLZIG_OLAF_2008	-3.770	(0.231)	***	-0.145	(0.001)	***
2008 Other GC	KRAHN_BRENT_2008	-2.289	(0.809)	***	-0.131	(0.008)	***
2008 Other GC	LABARBERA_JASON_2008	-3.713	(0.141)	***	-0.147	(0.001)	***
2008 Other GC	LACOSTA_DANIEL_2008	-4.896	(0.689)	***	-0.147	(0.001)	***
2008 Other GC	LALIME_PATRICK_2008	-3.723	(0.146)	***	-0.146	(0.001)	***
2008 Other GC	LECLAIRE_PASCAL_2008	-3.409	(0.179)	***	-0.143	(0.001)	***
2008 Other GC	LEGACE_MANNY_2008	-3.539	(0.142)	***	-0.146	(0.001)	***
2008 Other GC	LEHTONEN_KARI_2008	-3.940	(0.111)	***	-0.151	(0.001)	***
2008 Other GC	LEIGHTON_MICHAEL_2008	-3.923	(0.172)	***	-0.147	(0.001)	***
2008 Other GC	LUNDQVIST_HENRIK_2008	-4.063	(0.106)	***	-0.154	(0.001)	***
TCC 2008 GC	LUONGO_ROBERTO_2008	-4.014	(0.113)	***	-0.152	(0.001)	***
2008 Other GC	MACDONALD_JOEY_2008	-3.856	(0.111)	***	-0.151	(0.001)	***
2008 Other GC	MANNINO_PETER_2008	-3.831	(0.376)	***	-0.145	(0.001)	***
TCC 2008 GC	MASON_STEVE_2008	-3.959	(0.107)	***	-0.152	(0.001)	***
2008 Other GC	MASON_CHRIS_2008	-3.954	(0.112)	***	-0.152	(0.001)	***
2008 Other GC	MCELHINNEY_CURTIS_2008	-3.579	(0.221)	***	-0.144	(0.001)	***
2008 Other GC	MCKENNA_MIKE_2008	-3.650	(0.177)	***	-0.145	(0.001)	***
2008 Other GC	MILLER_RYAN_2008	-3.991	(0.109)	***	-0.152	(0.001)	***
2008 Other GC	MONTOYA_AL_2008	-4.178	(0.441)	***	-0.146	(0.001)	***

		Logistic Regression			Marginal Effects		
Variable Type	Variable	Coef.	Std. Err.		Coef.	Std. Err.	
2008 Other GC	NABOKOV_EVGENI_2008	-3.955	(0.113)	***	-0.152	(0.001)	***
2008 Other GC	NEUVIRTH_MICHAL_2008	-3.698	(0.357)	***	-0.144	(0.001)	***
2008 Other GC	NIEMI_ANTTI_2008	-3.516	(0.396)	***	-0.143	(0.001)	***
2008 Other GC	NIITTYMAKI_ANTERO_2008	-3.977	(0.139)	***	-0.149	(0.001)	***
2008 Other GC	NORRENA_FREDRIK_2008	-3.437	(0.254)	***	-0.143	(0.001)	***
2008 Other GC	OSGOOD_CHRIS_2008	-3.648	(0.115)	***	-0.148	(0.001)	***
2008 Other GC	PAVELEC_ONDREJ_2008	-3.615	(0.195)	***	-0.144	(0.001)	***
2008 Other GC	POGGE_JUSTIN_2008	-3.031	(0.212)	***	-0.140	(0.001)	***
2008 Other GC	PRICE_CAREY_2008	-3.849	(0.109)	***	-0.151	(0.001)	***
2008 Other GC	QUICK_JONATHAN_2008	-3.996	(0.124)	***	-0.150	(0.001)	***
2008 Other GC	RAMO_KARRI_2008	-3.630	(0.134)	***	-0.146	(0.001)	***
2008 Other GC	RAYCROFT_ANDREW_2008	-3.639	(0.132)	***	-0.147	(0.001)	***
2008 Other GC	RINNE_PEKKA_2008	-4.027	(0.118)	***	-0.152	(0.001)	***
2008 Other GC	ROLOSON_DWAYNE_2008	-4.000	(0.107)	***	-0.154	(0.001)	***
2008 Other GC	SABOURIN_DANY_2008	-3.813	(0.168)	***	-0.146	(0.001)	***
2008 Other GC	SANFORD_CURTIS_2008	-3.871	(0.184)	***	-0.146	(0.001)	***
2008 Other GC	SCHNEIDER_CORY_2008	-3.377	(0.247)	***	-0.143	(0.001)	***
2008 Other GC	SMITH_MIKE_2008	-3.768	(0.114)	***	-0.149	(0.001)	***
2008 Other GC	STEPHAN_TOBIAS_2008	-3.432	(0.219)	***	-0.143	(0.001)	***
2008 Other GC	TELLQVIST_MIKAEL_2008	-3.863	(0.165)	***	-0.147	(0.001)	***
2008 Other GC	THEODORE_JOSE_2008	-3.732	(0.105)	***	-0.151	(0.001)	***
2008 Other GC	THOMAS_TIM_2008	-4.224	(0.119)	***	-0.153	(0.001)	***
2008 Other GC	TORDJMAN_JOSH_2008	-3.359	(0.476)	***	-0.142	(0.002)	***
2008 Other GC	TOSKALA_VESA_2008	-3.709	(0.107)	***	-0.150	(0.001)	***
2008 Other GC	TURCO_MARTY_2008	-3.786	(0.099)	***	-0.153	(0.001)	***
2008 Other GC	VARLAMOV_SIMEON_2008	-4.089	(0.338)	***	-0.146	(0.001)	***
2008 Other GC	VOKOUN_TOMAS_2008	-4.082	(0.108)	***	-0.154	(0.001)	***
TCC 2008 GC	WARD_CAM_2008	-4.093	(0.110)	***	-0.154	(0.001)	***
2008 Other GC	WEEKES_KEVIN_2008	-3.940	(0.202)	***	-0.146	(0.001)	***
2008 TCC PC	BEAUCHEMIN_FRANCIOS_2009	12.474	(0.978)	***	0.120	(0.072)	

Variable Type	Variable	Logistic Regression			Marginal Effects		
		Coef.	Std. Err.		Coef.	Std. Err.	
2008 TCC PC	BERGERON_PATRICE_2009	12.562	(0.883)	***	0.247	(0.059)	***
2008 TCC PC	BOUWMEESTER_JAY_2009	13.048	(1.126)	***	0.066	(0.073)	
2008 TCC PC	BOYLE_DAN_2009	12.519	(0.905)	***	-0.010	(0.026)	
2008 TCC PC	BURNS_BRENT_2009	11.687	(1.306)	***	-0.005	(0.076)	
2008 TCC PC	CARTER_JEFF_2009	12.149	(0.875)	***	0.163	(0.045)	**
2008 TCC PC	CLEARY_DANIEL_2009	12.385	(0.925)	***	0.205	(0.072)	**
2008 TCC PC	CROSBY_SIDNEY_2009	12.595	(0.845)	***	0.360	(0.049)	***
2008 TCC PC	DOAN_SHANE_2009	12.091	(0.898)	***	-0.053	(0.017)	*
2008 TCC PC	DOUGHTY_DREW_2009	13.342	(0.917)	***	0.119	(0.053)	
2008 TCC PC	GAGNE_SIMON_2009	11.262	(1.077)	***	0.003	(0.055)	
2008 TCC PC	GETZLAF_RYAN_2009	12.523	(0.906)	***	0.238	(0.069)	**
2008 TCC PC	GREEN_MIKE_2009	12.829	(0.904)	***	0.312	(0.078)	***
2008 TCC PC	HAMHUIS_DAN_2009	13.174	(0.981)	***	0.276	(0.107)	*
2008 TCC PC	HEATLEY_DANY_2009	14.157	(0.951)	***	0.304	(0.057)	***
2008 TCC PC	IGINLA_JAROME_2009	12.646	(0.868)	***	0.320	(0.061)	***
2008 TCC PC	KEITH_DUNCAN_2009	12.901	(0.919)	***	0.042	(0.039)	
2008 TCC PC	LECAVALIER_VINCENT_2009	12.215	(0.907)	***	0.168	(0.059)	*
2008 TCC PC	LUCIC_MILAN_2009	13.284	(1.128)	***	0.381	(0.180)	
2008 TCC PC	MARLEAU_PATRICK_2009	12.551	(0.860)	***	0.349	(0.061)	***
2008 TCC PC	MCDONALD_ANDY_2009	12.819	(0.877)	***	0.320	(0.063)	***
2008 TCC PC	MORROW_BRENDEN_2009	12.250	(0.912)	***	0.185	(0.064)	**
2008 TCC PC	NASH_RICK_2009	12.520	(0.861)	***	0.265	(0.049)	***
2008 TCC PC	NIEDERMAYER_SCOTT_2009	12.574	(0.974)	***	0.140	(0.075)	
2008 TCC PC	PERRY_COREY_2009	12.236	(0.877)	***	0.198	(0.051)	***
2008 TCC PC	PHANEUF_DION_2009	12.435	(0.949)	***	0.177	(0.076)	
2008 TCC PC	PRONGER_CHRIS_2009	12.723	(0.986)	***	0.243	(0.102)	*
2008 TCC PC	RICHARDS_MIKE_2009	12.642	(0.875)	***	0.295	(0.061)	***
2008 TCC PC	ROBIDAS_STEPHANE_2009	12.590	(0.922)	***	-0.001	(0.031)	
2008 TCC PC	ROY_DEREK_2009	12.396	(0.912)	***	-0.024	(0.025)	
2008 TCC PC	SEABROOK_BRENT_2009	12.428	(1.010)	***	0.111	(0.077)	

		Logistic Regression			Marginal Effects		
Variable Type	Variable	Coef.	Std. Err.		Coef.	Std. Err.	
2008 TCC PC	SHARP_PATRICK_2009	12.332	(0.877)	***	0.203	(0.051)	***
2008 TCC PC	SPEZZA_JASON2009	12.070	(0.907)	***	0.163	(0.058)	*
2008 TCC PC	SMYTH_RYAN_2009	12.346	(0.925)	***	0.158	(0.064)	
2008 TCC PC	STLOUIS_MARTIN_2009	12.256	(0.982)	***	-0.038	(0.030)	
2008 TCC PC	STAAL_ERIC_2009	11.735	(0.913)	***	0.074	(0.045)	
2008 TCC PC	STAAL_JORDAN_2009	12.449	(0.889)	***	0.220	(0.059)	**
2008 TCC PC	STAAL_MARC_2009	13.002	(1.062)	***	0.235	(0.125)	
2008 TCC PC	THORNTON_JOE_2009	12.408	(0.927)	***	-0.022	(0.027)	
2008 TCC PC	TOEWS_JONATHAN_2009	12.507	(0.887)	***	0.244	(0.061)	***
2008 TCC PC	WEBER_SHEA_2009	12.426	(0.921)	***	-0.020	(0.027)	
2009 Other GC	ANDERSON_CRAIG_2009	-4.114	(0.133)	***	-0.151	(0.001)	***
2009 Other GC	AULD_ALEX_2009	-3.869	(0.197)	***	-0.146	(0.001)	***
2009 Other GC	BACKSTROM_NIKLAS_2009	-3.839	(0.134)	***	-0.149	(0.001)	***
2009 Other GC	BIRON_MARTIN_2009	-3.954	(0.178)	***	-0.147	(0.001)	***
2009 Other GC	BOUCHER_BRIAN_2009	-3.878	(0.186)	***	-0.146	(0.001)	***
TCC 2009 GC	BRODEUR_MARTIN_2009	-4.233	(0.144)	***	-0.151	(0.001)	***
2009 Other GC	BRYZGALOV_ILJA_2009	-4.146	(0.213)	***	-0.147	(0.001)	***
2009 Other GC	BUDAJ_PETER_2009	-4.217	(0.256)	***	-0.147	(0.001)	***
2009 Other GC	CLEMMENSEN_SCOTT_2009	-3.757	(0.200)	***	-0.145	(0.001)	***
2009 Other GC	CONKLIN_TY_2009	-4.083	(0.196)	***	-0.147	(0.001)	***
2009 Other GC	DANIS_YANN_2009	-4.327	(0.483)	***	-0.146	(0.001)	***
2009 Other GC	DIPIETRO_RICK_2009	-3.303	(0.549)	***	-0.142	(0.002)	***
2009 Other GC	DROUINDESLAURIERS_JEFF_2009	-4.362	(0.447)	***	-0.146	(0.001)	***
2009 Other GC	ELLIOTT_BRIAN_2009	-3.885	(0.159)	***	-0.147	(0.001)	***
2009 Other GC	ELLIS_DAN_2009	-4.243	(0.182)	***	-0.148	(0.001)	***
2009 Other GC	ERSBERG_ERIK_2009	-4.123	(0.344)	***	-0.146	(0.001)	***
TCC 2009 GC	FLEURY_MARCANDRE_2009	-4.068	(0.144)	***	-0.150	(0.001)	***
2009 Other GC	GARON_MATHIEU_2009	-3.931	(0.177)	***	-0.147	(0.001)	***
2009 Other GC	GIGUERE_JEANSEBASTIEN_2009	-3.917	(0.171)	***	-0.147	(0.001)	***
2009 Other GC	HALAK_JAROSLAV_2009	-4.464	(0.185)	***	-0.149	(0.001)	***

Variable Type	Variable	Logistic Regression			Marginal Effects		
		Coef.	Std. Err.		Coef.	Std. Err.	
2009 Other GC	HARDING_JOSH_2009	-3.791	(0.217)	***	-0.145	(0.001)	***
2009 Other GC	HEDBERG_JOHAN_2009	-4.225	(0.171)	***	-0.148	(0.001)	***
2009 Other GC	HILLER_JONAS_2009	-4.173	(0.150)	***	-0.150	(0.001)	***
2009 Other GC	HOWARD_JAMES_2009	-3.886	(0.250)	***	-0.145	(0.001)	***
2009 Other GC	HUET_CRISTOBAL_2009	-4.067	(0.158)	***	-0.149	(0.001)	***
2009 Other GC	JOHNSON_BRENT_2009	-4.194	(0.229)	***	-0.147	(0.001)	***
2009 Other GC	KHABIBULIN_NIKOLAI_2009	-3.988	(0.173)	***	-0.147	(0.001)	***
2009 Other GC	KIPRUSOFF_MIIKKA_2009	-4.304	(0.145)	***	-0.152	(0.001)	***
2009 Other GC	LABARBERA_JASON_2009	-4.261	(0.253)	***	-0.147	(0.001)	***
2009 Other GC	LALIME_PATRICK_2009	-4.064	(0.255)	***	-0.146	(0.001)	***
2009 Other GC	LECLAIRE_PASCAL_2009	-3.906	(0.166)	***	-0.147	(0.001)	***
2009 Other GC	LEGACE_MANNY_2009	-4.070	(0.204)	***	-0.147	(0.001)	***
2009 Other GC	LEIGHTON_MICHAEL_2009	-3.996	(0.194)	***	-0.147	(0.001)	***
2009 Other GC	LUNDQVIST_HENRIK_2009	-4.248	(0.139)	***	-0.151	(0.001)	***
TCC 2009 GC	LUONGO_ROBERTO_2009	-4.203	(0.146)	***	-0.151	(0.001)	***
2009 Other GC	MACDONALD_JOEY_2009	-3.768	(0.273)	***	-0.145	(0.001)	***
TCC 2009 GC	MASON_STEVE_2009	-3.801	(0.137)	***	-0.148	(0.001)	***
2009 Other GC	MASON_CHRIS_2009	-4.033	(0.148)	***	-0.149	(0.001)	***
2009 Other GC	MCELHINNEY_CURTIS_2009	-3.752	(0.258)	***	-0.145	(0.001)	***
2009 Other GC	MILLER_RYAN_2009	-4.412	(0.151)	***	-0.151	(0.001)	***
2009 Other GC	NABOKOV_EVGENI_2009	-4.297	(0.146)	***	-0.152	(0.001)	***
2009 Other GC	NEUVIRTH_MICHAL_2009	-4.057	(0.234)	***	-0.146	(0.001)	***
2009 Other GC	NIEMI_ANTTI_2009	-4.229	(0.217)	***	-0.147	(0.001)	***
2009 Other GC	NIITTYMAKI_ANTERO_2009	-4.182	(0.174)	***	-0.148	(0.001)	***
2009 Other GC	OSGOOD_CHRIS_2009	-3.808	(0.177)	***	-0.146	(0.001)	***
2009 Other GC	PAVELEC_ONDREJ_2009	-4.031	(0.151)	***	-0.149	(0.001)	***
2009 Other GC	PRICE_CAREY_2009	-4.072	(0.151)	***	-0.149	(0.001)	***
2009 Other GC	QUICK_JONATHAN_2009	-3.988	(0.142)	***	-0.150	(0.001)	***
2009 Other GC	RAYCROFT_ANDREW_2009	-3.910	(0.277)	***	-0.145	(0.001)	***
2009 Other GC	RINNE_PEKKA_2009	-4.047	(0.153)	***	-0.149	(0.001)	***

Variable Type	Variable	Logistic Regression			Marginal Effects		
		Coef.	Std. Err.		Coef.	Std. Err.	
2009 Other GC	ROLOSON_DWAYNE_2009	-4.071	(0.145)	***	-0.150	(0.001)	***
2009 Other GC	SCHNEIDER_CORY_2009	-4.387	(0.598)	***	-0.146	(0.001)	***
2009 Other GC	SMITH_MIKE_2009	-3.949	(0.150)	***	-0.148	(0.001)	***
2009 Other GC	THEODORE_JOSE_2009	-3.887	(0.164)	***	-0.147	(0.001)	***
2009 Other GC	THOMAS_TIM_2009	-4.113	(0.158)	***	-0.149	(0.001)	***
2009 Other GC	TOSKALA_VESA_2009	-3.708	(0.163)	***	-0.146	(0.001)	***
2009 Other GC	TURCO_MARTY_2009	-3.983	(0.141)	***	-0.149	(0.001)	***
2009 Other GC	VOKOUN_TOMAS_2009	-4.219	(0.138)	***	-0.151	(0.001)	***
TCC 2009 GC	WARD_CAM_2009	-4.080	(0.150)	***	-0.149	(0.001)	***

Note: ***, **, * indicates significance at the 1%, 5%, and 10% levels respectively.

Note: Marginal effect of isgoalhatstage1 is taken at the mean=0.104.

Note: TCC stands for Team Canada candidate, PC stands for player characteristics, and GC stands for goaltender characteristics.

Table 14. Summary of contribution to winning statistics and percentage of contribution to winning calculation.

2008 Rank	2009 Rank	2010 Men's Olympic Hockey Team Member	TCC Player	2008 TGSF	2008 TGSA	2008 Marg. Prob. of Scoring/Saving	2008 % of CW	2009 TGSF	2009 TGSA	2009 Marg. Prob. of Scoring/Saving	2009 % of CW
					Goaltenders						
5	1	Y	Martin Brodeur	NA	NA	-0.149	1.28%	NA	NA	-0.151	1.30%
4	2	Y	Roberto Luongo	NA	NA	-0.152	1.31%	NA	NA	-0.151	1.29%
2	3	Y	Marc-Andre Fleury	NA	NA	-0.153	1.32%	NA	NA	-0.150	1.29%
1	4	N	Cam Ward	NA	NA	-0.154	1.32%	NA	NA	-0.149	1.28%
3	5	N	Steve Mason	NA	NA	-0.152	1.31%	NA	NA	-0.148	1.27%
					Forwards						
7	1	Y	Jonathan Toews	0.371	0.368	0.270	0.89%	0.444	0.318	0.244	2.02%
3	2	Y	Patrick Marleau	0.491	0.441	0.208	1.31%	0.537	0.492	0.349	1.99%
17	3	Y	Sidney Crosby	0.417	0.487	0.214	0.17%	0.469	0.465	0.360	1.48%
22	4	Y	Patrice Bergeron	0.289	0.309	0.000	-0.17%	0.392	0.326	0.247	1.40%
18	5	N	Patrick Sharp	0.366	0.431	0.229	0.16%	0.425	0.363	0.203	1.28%
14	6	Y	Dany Heatley	0.379	0.438	0.237	0.27%	0.491	0.504	0.304	1.17%
8	7	Y	Rick Nash	0.414	0.414	0.246	0.88%	0.436	0.418	0.265	1.16%
26	8	Y	Brenden Morrow	0.280	0.388	0.000	-0.92%	0.375	0.350	0.185	0.82%
11	9	Y	Mike Richards	0.419	0.453	0.211	0.46%	0.447	0.485	0.295	0.81%
6	10	N	Ryan Smyth	0.457	0.425	0.240	1.22%	0.397	0.365	0.158	0.81%
1	11	Y	Ryan Getzlaf	0.489	0.418	0.202	1.47%	0.504	0.531	0.238	0.80%
4	12	Y	Corey Perry	0.476	0.418	0.183	1.25%	0.520	0.536	0.198	0.75%
21	13	N	Jason Spezza	0.370	0.427	0.109	-0.15%	0.475	0.472	0.163	0.68%
16	14	N	Jeff Carter	0.415	0.491	0.238	0.20%	0.511	0.519	0.163	0.65%
19	15	N	Jordan Staal	0.303	0.355	0.211	0.10%	0.368	0.401	0.220	0.42%
24	16	N	Daniel Cleary	0.358	0.397	0.000	-0.34%	0.372	0.400	0.205	0.41%
20	17	Y	Jarome Iginla	0.443	0.520	0.195	0.08%	0.402	0.492	0.320	0.33%
25	18	N	Shane Doan	0.336	0.470	0.234	-0.47%	0.419	0.361	-0.053	0.30%

2008 Rank	2009 Rank	2010 Men's Olympic Hockey Team Member	TCC Player	2008 TGSF	2008 TGSA	2008 Marg. Prob. of Scoring/Saving	2008 % of CW	2009 TGSF	2009 TGSA	2009 Marg. Prob. of Scoring/Saving	2009 % of CW
9	19	N	Simon Gagne	0.399	0.387	0.200	0.79%	0.402	0.411	0.000	-0.08%
15	20	N	Andy McDonald	0.313	0.355	0.230	0.26%	0.359	0.488	0.320	-0.12%
13	21	N	Vincent Lecavalier	0.370	0.411	0.196	0.27%	0.369	0.455	0.168	-0.21%
2	22	Y	Joe Thornton	0.480	0.450	0.276	1.40%	0.494	0.519	0.000	-0.21%
10	23	N	Martin St. Louis	0.398	0.402	0.213	0.69%	0.364	0.401	0.000	-0.31%
5	24	Y	Eric Staal	0.518	0.451	0.146	1.23%	0.497	0.535	0.000	-0.32%
12	25	N	Derek Roy	0.359	0.383	0.187	0.37%	0.361	0.422	0.000	-0.53%
23	26	N	Milan Lucic	0.302	0.419	0.305	-0.22%	0.225	0.362	0.000	-1.18%
			Defense								
4	1	Y	Chris Pronger	0.416	0.493	0.144	-0.15%	0.543	0.505	0.243	1.47%
15	2	N	Dan Hamhuis	0.433	0.586	0.000	-1.32%	0.562	0.587	0.276	1.12%
14	3	N	Brent Burns	0.333	0.472	0.000	-1.20%	0.480	0.415	0.000	0.56%
8	4	Y	Duncan Keith	0.559	0.600	0.000	-0.35%	0.569	0.509	0.000	0.52%
13	5	Y	Drew Doughty	0.391	0.496	0.000	-0.91%	0.461	0.414	0.000	0.40%
5	6	Y	Brent Seabrook	0.479	0.505	0.000	-0.22%	0.510	0.468	0.000	0.37%
1	7	N	Mike Green	0.518	0.485	0.291	1.58%	0.450	0.565	0.312	0.21%
2	8	Y	Dan Boyle	0.511	0.471	0.162	1.05%	0.562	0.548	0.000	0.12%
6	9	N	Stephane Robidas	0.433	0.470	0.000	-0.32%	0.445	0.437	0.000	0.07%
16	10	N	Francois Beauchemin	0.438	0.600	0.000	-1.39%	0.538	0.532	0.000	0.05%
3	11	Y	Shea Weber	0.502	0.536	0.190	0.54%	0.488	0.521	0.000	-0.29%
7	12	Y	Scott Niedermayer	0.433	0.535	0.143	-0.34%	0.486	0.606	0.000	-1.03%
10	13	N	Dion Phaneuf	0.542	0.592	0.000	-0.44%	0.418	0.566	0.000	-1.27%
11	14	N	Jay Bouwmeester	0.424	0.578	0.179	-0.68%	0.365	0.514	0.000	-1.28%
12	15	N	Robyn Regehr	0.411	0.492	0.000	-0.69%	0.378	0.542	0.000	-1.41%
9	16	N	Marc Staal	0.495	0.539	0.000	-0.38%	0.391	0.578	0.000	-1.61%