**Contests: Affirmative Action and Sabotage**

**Negative Characteristics in Contest Design Observed in Horse Racing in the United Kingdom in 2019**

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In partial fulfillment of the requirements for the degree of Master of Science in Economics of the Joint Program in Economics of the Technion – Israel Institute of Technology and the University of Haifa

**Submitted to the Senate of the Technion – Israel Institute of Technology**

**University of Haifa – The Graduate School**

**Cheshvan, 5781, Haifa, November 2020**

Table of Contents

[Abstract 4](#_Toc54810809)

[Introduction 5](#_Toc54810810)

[Considerations in a Contest Design 6](#_Toc54810811)

[Contest Success Function and Leveling the Playing Field 8](#_Toc54810812)

[Sabotage 11](#_Toc54810813)

[Horse Racing 12](#_Toc54810814)

[Study Design, Materials, and Procedures 13](#_Toc54810815)

[General Discussion 25](#_Toc54810816)

[References 26](#_Toc54810817)

# Abstract

Affirmative action is a policy designed to balance opportunities to meet opening conditions in competitive fields. Although such policies usually seek to support certain demographic groups, commonly referred to as “minorities” or “weakened groups” with relatively low socioeconomic status, they are also applied in sports, political campaigns, rent-seeking contests, and more. The goal of affirmative action is to improve the diversity of contest outcomes and to equalize opportunities between all levels of society. The literature shows that too much asymmetry among players causes incentive problems, resulting in reduced levels of general effort due to the “despair effect,” where weaker players have low expectations and no will to invest effort and stronger players feel no need to invest effort. In such cases, a contest designer might consider implementing an affirmative action policy, whether by weakening the strong players (handicapping) or by strengthening the weaker players (head start). This work examines whether affirmative action designed to reduce the gaps in the competitive world might by trying to encourage effort might actually motivate contestants to sabotage other contestants.

Using a natural experiment with data from horse racing in the United Kingdom in 2019, I demonstrate how affirmative action that handicaps favorite horses results in a more balanced playing field by giving weaker horses higher winning probabilities. I also demonstrate that cases of sabotage and negative behavior between riders are more prevalent in such races. Sabotage, usually by the leading jockeys, improves their position by an average of 0.99 placings. I also show that stronger riders (the top 5% of U.K. jockeys) are in general 4.5 times more involved in cases of interference between riders are regular jockeys.

# Introduction

A contest is a game in which the contestants invest high sunk costs, usually expressed as effort, while trying to win a prize. Examples can be found in sports, the economy, political campaigns, and almost countless other scenarios that meet the operating conditions of a contest.

Corchón and Serena (2018) classified contests into two large categories: those that occur naturally to resolve conflict (e.g., war) and those that are planned and organized by a contest designer to achieve a certain outcome. This paper addresses the latter.

Runkel (2006) suggested that a contest designer be selected whose revenue increases in proportion to the size of the audience, implying that the contest designer should address the desires of the audience, which often will be influenced by the contestants’ improved performance. A contest in which the contestants perform well is more attractive to the public. In this case, the variance in the abilities of contestants must be considered. Runkel showed that under certain assumptions, a marginal increase in the prize may improve both performance and competitive closeness, which will lead to greater revenue for the designer due to both of these (i.e., good performance and competitive proximity).

In a close contest or in any market where the variance in the quality is low and there is low price elasticity, the prizes will be distributed on the basis of relative and not absolute performance; in a structure in which there is only one winner, small differences in quality will be reflected in significant prize gaps (Loury & Fryer, 2004).

A field of heterogeneous players might lead to undesirable results, such as a low effort in performance (Chowdhury, Esteve-Gonzales, & Mukherjee 2019). The literature shows that too much asymmetry among players causes incentive problems that may reduce the overall level of effort. An uneven contest, where results are clear ex ante, might be less exciting to watch than a close contest.

This well-known problem has been addressed in many ways. Researchers have suggested diverse ways to level the playing field using policies such as affirmative action, known mostly for addressing ethical violations. This policy mainly supports weaker demographic groups and minorities.

Affirmative action policies can improve a contest by allowing equal probabilities to succeed *ex ante*, whether by weakening the strong players (handicapping) or by strengthening the weakened players (head start).

The purpose of affirmative action is to improve diversity in competition outcomes and allow equal opportunities for all parts of society. This policy is widely implemented throughout the world. However, its impact is still unclear, which undermines public support for this policy (Chowdhury et al., 2019).

This work examines whether a type of affirmative action designed to reduce the gaps in a competitive world might, in an attempt to encourage effort, also encourage competitors to sabotage other competitors.

When seeking to implement affirmative action aimed at improving diversity, the contest designer should examine how to level the playing field by choosing the right design, taking into account other factors that may influence the success or failure of such goals. For example, there may be an incentive to sabotage opponents when such a policy is implemented (Chowdhury & Brown, 2014; Lazear, 1989).

The world of horse racing, which has dozens of races daily, provides the scene for a natural experiment. In the majority of these races, corrective actions are taken to allow equal probability for contestants to win. This equestrian scene provides a real measurement of riders’ sabotage against each other, and hence, an opportunity to search for the common denominator or the relationship between sabotage and level of competitiveness.

The assumption is that reducing a priori differences between contestants will encourage effort but will also encourage sabotage as a strategy as competitors attempt to improve their position.

Studies on the subject have confirmed the hypothesis that a high level of competitiveness at the starting point (i.e., a low standard deviation of the implied win probabilities) may lead to intervention and sabotage between the various competitors and hence a possible decrease in general well-being (Brown & Chowdhury [2014]; Konrad [2003]); Lazear ]1989]).   
Drawing on insights from a review of the literature, the following chapters will discuss some of the characteristics of a contest and the dilemmas facing a contest designer. Following this, cases of sabotage in relation to affirmative action and competitive proximity this will be tested through empirical evidence from horse racing competitions.

# Considerations in a Contest Design

During preparations for a contest, a plan should be made that is suitable for the purpose of the contest. Purposes can vary: for example, making money by selling tickets, obtaining broadcasting rights, or perhaps increasing the bets in a gambling event. According to the literature, a contest designer is often someone whose earnings depend on the size of the audience that attends the event. A bigger audience will positively influence entrance fees and sponsorships. Therefore, the designer must relate to the size of the prize, the contest success function (CSF, the individual’s probability of winning the prize as a function of effort), and the structure of the contest. Most often, it seems that the rewards for the contest designer will be directly related to the effort invested by contestants.

Brown (2011) showed that large differences in skill may reduce efforts and that an outstanding performer in a contest will decrease the level of performance, implying that Tiger Woods earned millions more than he normally would have between 1999 and 2006 because of his opponents’ weaker performance whenever he participated in an event. Lim (2010) showed that in some cases a contest designer should consider the number of winners in an event. Addressing the question of how many winners and losers there should be in a contest, he showed that if competitors make social comparisons, more winners than losers can lead to a higher level of effort. Lim gave as an example marketing executives who often use contests to motivate their sales forces, service workers, and franchisees.

Szymanski (2003) showed how each contestant chooses an optimal effort for him or herself and that all contestants invest some positive effort. Szymanski demonstrated how an unequal contest could harm the overall effort and recommended that a contest designer try and level the playing field. If it is not possible to identify the various competitors, then perhaps considering an optimal prize and charging an entry fee could ensure a high level of contestants. It seems that sometimes entries into races with large cash prizes are determined by prior arrangement and aimed at a select group of athletes. Using data from a prestigious tennis tournament, Sunde (2007) showed that greater heterogeneity among contestants affects their incentive to exert effort. Sunde emphasized the importance of finding strategies to identify and allow evaluation of whether the intended incentives actually affect individual behavior.

Runkel (2006) suggested that competitive closeness has a significant impact on rewards. The variable he proposed as a measure of competitive closeness is the standard deviation of the implied win probabilities when the rationale that explains it is that the closer the probabilities of winning among contestants, the more uncertainty there is of the outcome of a game. Runkel examined how the addition of competitive closeness helped the contest designer decide what the optimal prize should be. In addition, according to Runkel, the distinction between effort costs of the various competitors should be examined. If the contest designer cannot distinguish between the different participants, and the designer’s rewards depend only on the quality of the performance, then a uniform increase in effort costs cannot be optimal because it will harm the overall quality of the performance. However, Runkel also showed that in situations where it is not possible to identify and discriminate between the various competitors, it is possible to raise the costs of effort in exchange for competitive closeness, although performance may be impaired (e.g., a ceiling in political campaigns; a maximum engine capacity in Formula One races). On the other hand, if the cost of discrimination between the various competitors is not high, and the designer is able to discriminate between the various contestants, then imposing restrictions on strong players (handicapping) may be optimal.

Corchón and Serena (2018) suggested that a designer could choose to maximize the total effort by leveling the playing field perfectly (i.e., by giving some advantage to weaker players, as they are strategic complements). Raising the effort with one will encourage an increase in the effort of the other.

# Contest Success Function and Leveling the Playing Field

This paper does not try to design an optimal contest but rather seeks to empirically check for consequences that align with some written design.

This section on the CSF is based on a paper by Corchón and Serena (2018). Its purpose is to include a theoretical view of the most popular CSFs used to meet the designers’ objectives by managing players’ incentives to invest effort. The axioms related to the CSF include an independence from irrelevant alternatives (e.g., the outcome of two player contests does not depend on the effort of players not participating in the contest). Winning probabilities depend on the ratio of the players’ efforts, and winning probabilities depend on the difference in efforts. For more on the axiomatic approach, see Skaperdas (1996).

In general, a contest can be considered a game in which players compete using strategies that are expressed in terms of effort, prize, and payoffs (expected utility).

A group of players is denoted as , effort is denoted as , prize as and payoffs as .

In addition, it is assumed that a player is risk neutral and has a linear cost function, and that the marginal cost equals 1. Then the expected utility for a player *i* can be calculated as follows: 

In accordance with Corchón and Serena (2018) this paper usesa common CSF, the all-pay auction (APA), introduced by Hillman and Riley (1989). The APA takes the following form: 

It is notable that there are no equilibria in pure strategies as long as a contestant is not the winner, in which case the contestant should decrease their efforts to 0. The highest effort considered by the winner should be a small epsilon more than the second highest effort. That small cost is always a reason to deviate.

The lottery CSF, introduced by Tullock (1980), takes the form of . This CSF is homogeneous at degree 0, where  is not sensitive to a specific unit measurement of effort.

The final and most common CSF used to justify leveling the playing field is the logit CSF proposed by Dixit (1987):

,

where measures the impact of  on the outcome of a contest.

Szymanski (2003), Mealem and Nitzan (2016), and Chowdhury et al. (2019) offered a description of an effort impact function, introduced by Tullock (1980). In their case, the logit CSF can take the form of , where  is the player’s budget; and  is the impact function, which reflects the effect of player *i* on a contest, given their effort. The parameter  is interpreted as noise or a measure of the discriminatory power of the CSF; and lead to a completely random outcome of a contest. The outcome of the former takes the form of a lottery CSF, whereas the outcome of the latter takes a form of APA. This means that as  increases, the noise in the contest outcome decreases, leading to contest results that are clearer ex ante. This shows that under the logit CSF, assuming the designer has the ability to choose , as  increases, a player expending more effort is increasing their probability of winning. Strong players have incentives to invest effort. Chowdhury et al. (2019) and Szymanski (2003), Mealem and Nitzan (2016) showed that some positive amount of noise in the effort impact function is needed to maximize total effort, and optimal levels of noise depend on the shape of the cost function.

Chowdhury et al. (2019) defined a mechanism of leveling the playing field as the cost of effort, where altering costs can handicap the favorites or give a head start to weaker players; this strategy aims to equalize the winning probabilities of all players if they invest the same effort cost.

By implementing a multiplicative bias in the impact function, where all players receive equal treatment, the cost of effort is assumed to be linear () and is multiplied by the same alpha () compared with affirmative action where the weights attached to the players’ effort are in proportion to their marginal cost () and under an *n*-player contest where , affirmative action will keep all players active in the game. In contrast, under equal treatment, there is a positive probability that only some of the players will stay active, incentivizing the strong players to invest more effort. This may result in higher total effort under equal treatment, though Chowdhury et al. (2019) suggested that when effort costs are not too heterogeneous to begin with, affirmative action as a policy is likely to deliver higher total effort.

Corchón and Serena (2018) proposed using the lottery CSF and adding an , as in , to perfectly level the playing field. This would give an advantage to weaker players and maximize the total effort: it would encourage strong players to invest more effort, as they are strategic complements.

This paper shows empirically that handicapping does indeed lead to a closer competition with uncertain outcomes, but it comes with a negative byproduct in the form of sabotage, as suggested by Brown and Chowdhury (2014) and Lazear (1989). Horse races are used as a contest that supplies measurements of effort, probabilities of winning, sabotage as interference between riders, and other measurements of the prior abilities of contestants. A designer of a horse race would be the handicapper, who tries to level the playing field by adding weight for strong horses and leveling to a degree the winning probabilities at the beginning of a race. Horse racing is designed in such a way that horses compete against other horses from a similar level under a range of handicaps (i.e., effort costs are not too heterogeneous to begin with).

# Sabotage

Lazear (1989) showed that increasing rewards might lead to negative behavior that reduces the output of a rival. It seems that when a competitor’s earnings are based on relative performance, there are incentives to invest effort in making their opponents fail, even when the total output is reduced. As del Corral, Prieto-Rodríguez, and Simmons (2010) demonstrated, an increase of one point in the Spanish football league per winning game increased cases of red cards (sabotage punishable by the dismissal of a player) within teams in the winning position. They also showed that there was a higher probability of receiving red cards toward the end of a match regardless of the position of the team.

Konrad (2003) demonstrated how an interest group that is lobbying for a discussion that will benefit them and is competing with other groups on a particular matter will invest effort in what is considered in the literature a rent-seeking contest in the hope that it will increase their probability of winning a prize and decrease the probabilities of their rivals. This is considered a standard rent-seeking effort. In addition, the interest group might invest some negative effort (sabotage) to decrease the probability of the group being sabotaged and increase the probabilities of all other groups.

This negative effort has been shown to decrease as the number of competing groups increases, as it is costly and benefits all other contestants. Grad, Lettl, and Riedl (2020) also demonstrated that strategic behavior influences the outcomes of a contest and that top contestants might be both culprits and victims of sabotage.

Cases of sabotage appear at political events, in marketing campaigns, and in sports. Although it is known that investing effort will increase a contestant’s probability of winning a prize, it has been shown by Chowdhury and Brown (2017) and Lazear (1989) that destructive behavior such as sabotage may also increase the probabilities in favor of the saboteur. Chowdhury and Gürtler (2015) described it as an invested cost that harms the opponent’s probability of winning a prize. It seems that most sabotage cases are directed at the better opponent and will indeed hurt the overall effort of the competitors. Sabotage may also reduce the effectiveness of the competition organizer’s policy. Chowdhury and Gürtler mentioned that while contestants will invest resources in order to win the prize, there are those who will also invest in the opponent’s not winning the same prize. Examples were given of businesses harming competing businesses by hiring salespeople whose main job is to track competitors’ salespeople and to motivate potential buyers to not deal with the competitors (Friedman, 1998). Another example looks at how Microsoft engineers hid information from each other in order to outperform the other engineers and receive better evaluations from the company (Oremus, 2013).

Munster (2007) examined cases of sabotage in a selection of contests with heterogeneous participants and found that contestants can equalize their probabilities of winning the contest, even if there are differences in their skills. Furthermore, the author showed that it might spur the less talented contestants to compete, as incentives for the good contestants will decrease if they realize that the more talented they are, the more they will experience sabotage. Hence, using a tournament such as a promotional contest, a political contest, a rental contest, and other contests of this kind might lead to the selection of a non-talented contestant.

This study, which examines horse racing, will refer to any act of interference that was noticed by stewards and any riding offense that was declared an act of sabotage.

# Horse Racing

A natural starting point for the analysis in this paper would be an introduction to the equestrian world and horse racing in particular.

Most horse racing in the United Kingdom is handicap racing. In such a race, every horse gets an added weight related to its abilities. This approach provides equal probabilities of winning *ex ante*. The handicap ratings will dictate in which category the horse may compete. The categories are from A to G: A represents the best category, and G represents the weakest one. Every horse gets a handicap rating right after its third performance, and from that point on, its official rating will change in relation to its successes. Other factors considered by handicappers might be the ground the horse is running on, old injuries, and anything else that might influence the way the horse will perform that day.

A high-rated horse is a good horse and therefore will carry more weight than a low-rated horse. Each level is worth 1 lb (0.45 kg) that the horse must carry (for more information about official handicap rating, please check the British Horseracing Authority (BHA) website: <https://www.britishhorseracing.com>).

The betting market is one of the main reasons for the popularity of a horse racing event. Until recently, gambling shops were the mainstay of the horse racing gambling activity (Smith & Vaughan Williams, 2010). At the end of the 1960s, most of the 16,000 or so betting shops in the United Kingdom were owned by independent betting agents. Since then, these shops have been held by a small number of bookmaker chains.

These agents offer prices or “odds” that dictate the conditions for betting on the event, usually based on a fraction, when the sum of the probabilities is usually higher than one. The surplus unit, mostly called the “over round,” will embody within it the guaranteed return to the agent. The average size for 45,335 races in this study was 26.21% when there was an additional profit (or loss), with the dividend on each horse resulting from the volume of bets on it.

These betting markets offer some assets that appear to contradict the principles of efficiency and rationality (Sauer, 1998) when they usually yield cumulative negative returns; moreover, economists have confirmed a longshot-favorite bias, in which better horses are underrated and horses with long odds are overrated; the “hot hand effect” occurs when bettors overestimate positive performance.

In Australia, New Zealand, the United Kingdom, and other European countries such as France and Italy, the dominant betting method is a fixed odds system set by the betting agent (Ziemba, Lo, & Hausch 1994). The system works as follows: No bet can be made until the bookmaker posts the odds so that the initial odds do not depend on the market response. The bookmaker offers odds that can change during the betting period, but the gamblers are included in these odds, even if the odds change thereafter.

Under certain warnings, the odds set by the bookmakers can be seen as a subjective probability forecast, but a possible difficulty for this assumption is that the fixed odds of the betting agents are often inconsistent with the axioms of probability theory. For example, the total probability for the winning horses is higher than one.

Although organized betting has a negative return for most players, if not all, the odds offered by bookmakers must be tempting enough to attract bets, and the reasonable impact that competition has on this market cannot be ignored. Many agents operate so that unattractive bets will not be competitive in the market, and as a result gamblers miss opportunities for additional revenue. There is no doubt that psychological theories describing probabilistic biases are widely expressed in this market (Ayton 1997).

# Study Design, Materials, and Procedures

Brown and Chowdhury (2014) showed that reducing a priori differences between contestants by handicapping will result in an equilibrium with high effort, greater chances of weaker players winning, and more incidents of sabotage. Brown and Chowdhury first produced a model representing a theoretical benchmark based on the model designed by Lazear (1989), and followed this with an empirical review on horse racing in the United Kingdom. This paper will emulate this work by presenting new data with some minor changes, such as the use of the actual distance of a jockey to the winning horse as a predictor of the independent variable (“is the jockey a saboteur”), showing that it is mostly the competitive leading jockeys who participate in negative actions of this kind.

In addition to what is found in the relevant literature, this work adds a certain character to the saboteur in view of the fact that the top 5% of jockeys in 2019 were significantly more involved in cases of interference than the rest of the competing jockeys. It is not only the leading jockeys in a race, but rather the top jockeys of an entire year who can be assumed to act more aggressively toward competing colleagues.

Data

Data on all horse racing in the United Kingdom is available on the BHA website, where it is also possible to find each incident of interference between riders under a category of stewards’ reports: <https://www.britishhorseracing.com/racing/stewards-reports>.

Data on the position of horse and rider, horses’ handicap ratings, distance between horses, betting odds, distance of a race, and the prize money in a race is from an English betting company, Proform Racing, for which I purchased software that allowed me to view historical data for the past 19 years: <https://www.proformracing.com>.

Figure 1 shows an example of the output from a Proform racing file.

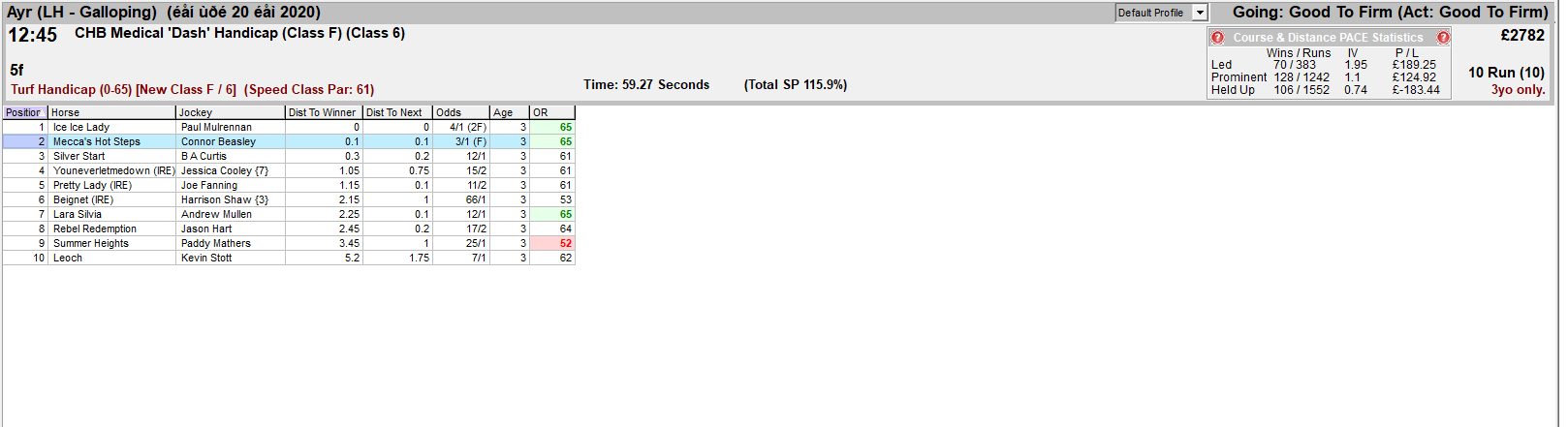


Figure 1. Output from a Proform racing file.

The data collected came only from racetracks with at least one incident of interference during the year. In order to avoid noisy data, the same line of stewards and rules was maintained. Data was collected data on 1619 horse races and 15,206 riders (Table 1).

Table 1. Summary statistics for 1619 horse races in the UK in 2019.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  |  | **Summary Statistics** |
| Flat  (*N*=1,393) | Jump  (*N*=226) | Non-handicap (*N*=525) | Handicap  (*N*=1,094) | All (*N*=1,619) | **Races** |
| 10.58186  (3.367939) | 11.1953  (6.577315) | 9.727881  (3.528647) | 11.05084  (4.031867) | 10.66  (3.93643) | No. of runners |
| 10,353.31  (38,390.95) | 27,968.17  (75,802.01) | 19,462.62  (65,989.2) | 9,745.128  (32,662.35) | 12,609  (45,336.66) | Prize money (GBP) |
| 1,803.898  (612.8448) | 4,521.857 (963.7516) | 2,048.969  (1,077.639) | 2,197.779  (1,147.009) | 2,153.868  (1,128.99) | Distance |
| Flat | Jump | Non-handicap | Handicap | All | **Horses** |
| 4.410301  (1.894673) | 7.23773  (2.110073) | 3.781146  (1.89898) | 5.187704  (2.101953) | 4.772656  (2.1424) | Age |
| 18.52829  (24.65012) | 20.99674 (29.74687) | 26.86497  (36.9666) | 15.48574  (17.4128) | 18.84353  (25.37398) | Odds |

Note: Top panel shows race statistics. Bottom panel shows horse statistics. Measures are means and standard deviations (in parentheses).

# Analysis

The first part of this analysis focuses on confirming whether handicapping succeeds in leveling the field prior to the beginning of the race. For this, a procedure similar to that of Brown and Chowdhury (2014) was followed.

H1: Handicap racing will lead to more uncertainty in anticipating results and results ex post.

Testing this hypothesis, regression was run on an indicator variable equaling 1 if the favorite won the race and 0 if otherwise against an indicator variable equaling 1 if the horse was running in a handicap race and 0 if otherwise. This suggests that if the favorite wins less in handicap racing, these events do not follow the odds as determined and expected by the bookkeeper.

The test result was significant: (, *p* < 0.00). A control variable was added to regression 2: (, *p* < 0.00). See Tables 2 and 3.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Table 2. Logistic Regression Analysis. Dependent Variable: Favorite Wins = 1. | | | | | | |
| Predictor |  |  |  | *p* | No. of obs. |  |
| Handicap | −0.500990 | 0.1086681 | 0.6059303 | 0.000 | 1619 | 0.0099 |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Table 3. Logistic Regression Analysis. Dependent Variable: Favorite Wins = 1. | | | | | | | |
| Predictor |  |  |  | *p* | No. of obs. |  | Hosmer–Lemeshow | |
| Handicap | −0.432545 | 0.1104948 | 0.6488554 | 0.000 | 1619 | 0.0165 | *P*=0.3420 |
| No. of runners | −0.587502 | 0.0160185 | 0.9429423 | 0.000 |  |  |  |

To further investigate whether handicapping does its job in getting a race closer together *ex ante* and *ex post*, two dependent variables were used: the standard deviation of the odds and the standard deviation of the distance between the horses at the finish line, respectively, as a way of measuring how even the race is.

H1: The standard deviation of the odds in handicap racing is smaller.

H2: The standard deviation of the distance between the horses at the finish line in handicap racing is smaller.

The negative coefficient of the handicap as a predictor on both independent variables indicates that handicap racing leads to a smaller spread in odds before the race and results in horses being closer to each other at the end of a race, showing that handicap racing is more even than non-handicap racing. Both measures were significant: (*F*1,1617 = 387.19, *p* = 0.00) and (*F*1,1608 = 14.10, *p* = 0.00), respectively. Control variables were added in regressions 5 and 6, and the results were found to be robust.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table 4. Logistic Regression Analysis. Dependent Variable: Standard Deviation of the Odds. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Handicap | −13.78322 | 0.7005478 | 0.000 | 1619 | 0.1932 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table 5. Logistic Regression Analysis. Dependent Variable: Standard Deviation of the Odds. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Handicap | −16.70791 | 0.6775615 | 0.000 | 1619 | 0.3130 |
| Win prize money | −0.000208 | 0.00001 | 0.038 |  |  |
| No. of runners | 1.148823 | 0.0926833 | 0.000 |  |  |
| Class rate | 2.105674 | 0.2516379 | 0.000 |  |  |
| Distance | 0.002193 | 0.0004729 | 0.000 |  |  |
| Jump race | −2.805747 | 1.522723 | 0.066 |  |  |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table 6. Logistic Regression Analysis. Dependent Variable: Standard Deviation of Distance between Horses at FLnish line. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Handicap | −1.622607 | 0.427465 | 0.000 | 1619 | 0.088 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table 7. Logistic Regression Analysis. Dependent Variable: Standard Deviation of Distance between Horses at Finish Line. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Handicap | −3.032781 | 0. 3704592 | 0.000 | 1616 | 0.3229 |
| Win prize money | −0.000208 | 0.00001 | 0.007 |  |  |
| No. of runners | 0.4003202 | 0.0506749 | 0.000 |  |  |
| Class rate | 0. 4786002 | 0.137584 | 0.001 |  |  |
| Distance | 0.0037074 | 0..0002586 | 0.000 |  |  |
| Jump race | 1.432244 | 0.8325544 | 0.086 |  |  |

In accordance with the work of Brown and Chowdhury (2014), I continued by checking the correlation between the odds determined by the bookkeeper and those determined by the public as an indicator of expectations, as smaller odds represent expectations for a higher ranking horse.

It seems that both handicap and non-handicap odds are correlated with the positioning of the horse. However, non-handicap odds show a stronger relationship to results with a correlation of 0.444 compared to a correlation of 0.382 in handicap races, indicating more uncertain outcomes.

The second part of the analysis was to determine whether interference happens more in handicap than in non-handicap racing.

H1: Sabotage, presented as cases of interference, is more present in handicap racing than in non-handicap racing.

An indicator equaling 1 if there was interference by a jockey and 0 if otherwise was regressed against a variable equaling 1 if the race was a handicap race and 0 if otherwise. As expected, the result shows a positive relationship (, *p* < 0.00).

In the following regression (Table 8), control variables were included and revealed a negative relationship between the odds and the interference. As before, I found a positive eﬀect of handicapping on sabotage in a race (, *p* < 0.00).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Table 8. Logistic Regression Analysis. Dependent Variable: Jockey is a Saboteur = 1. | | | | | | | |
| Predictor |  |  |  | *p* | No. of obs. |  | Hosmer–Lemeshow |
| Handicap | 0. 4016528 | 0. 165933 | 1.494292 | 0.015 | 15,206 | 0.0218 | *P*=0.3283 |
| No. of runners | −0.0283804 | 0. 016984 | 0..9720185 | 0.095 |  |  |  |
| Odds by number | −0.0230714 | 0.005217 | 0.9771927 | 0.000 |  |  |  |
| Official rating | 0.0035484 | 0.0020747 | 1.003555 | 0.087 |  |  |  |

As mentioned in previous work, the strong correlation between interference and handicap racing might give a wrong impression of causality, while an act of interference may derive from the tight racing that handicapping provides. Therefore, the effect of the closeness of the race was measured, as well as the effect of handicapping and non-handicapping, on interference as it appears in horse racing in the UK.

H1: Closer races, both handicap and non-handicap, have more cases of sabotage.

A variable used to measure the closeness of the race is the standard deviation of the odds. In regression 1, I regressed interference on the standard deviation of the odds with an expected negative relationship between tighter racing and interference (, *p* = 0.0382).

In the following regressions I have separated handicapped races from non-handicapped races. The regression reported a significant result (, *p* = 0.0746); the negative coefficient of −0.17 reflects the nature of the relationship between tightness of a race and interference.

I found a similar significant result in non-handicapped racing with a negative coefficient of −0.2 ( , *p* = 0.0216).

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| Table 9. Logistic Regression Analysis. Dependent Variable: Jockey is Saboteur = 1 for ARl races. | | | | | | | |
| Predictor |  |  |  | *P* | No. of obs. |  | Hosmer–Lemeshow |
| SD of odds | −0.0247344 | 0. 00575 | 1.494292 | 0.000 | 15,206 | 0.0077 | *P*=0.6882 |

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| Table 10. Logistic Regression Analysis. Dependent Variable: Jockey is Saboteur = 1 for Handicapped Races. | | | | | | | |
| Predictor |  |  |  | *P* | No. of obs. |  | Hosmer–Lemeshow |
| SD of odds | −0.0170738 | 0.0085468 | 1.494292 | 0.046 | 10,719 | 0.0019 | *P*=0.7801 |

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| Table 11. Logistic Regression Analysis. Dependent Variable: Jockey is Saboteur = 1 for Non−Handicapped races. | | | | | | | |
| Predictor |  |  |  | *p* | No. of obs. |  | Hosmer–Lemeshow |
| SD of odds | −0.0203092 | 0. 0094657 | 1.494292 | 0.032 | 4487 | 0.0089 | *P*=0.6913 |

As in previous research, these results raise a question regarding the incentive that Lazear’s (1989) model suggests. Is the incentive the reason for interference? Or is interference just something that jockeys do when a race provides them with a closer field?

While collecting data, a relationship between the saboteur (the jockey who interfered) and their position in the race could not be overlooked. To measure this, a new independent variable was added: distance to the winner.

H1: Cases of sabotage appear more at the top of the race (i.e., with the leading horses).

As expected, there is a strong negative relationship between interference and the distance to the winner in the race in general (, *p* = 0.00) and specifically in handicap and non-handicap races ( , *p* = 0.000;, *p* = 0.000), respectively.

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| Table 12. Logistic Regression Analysis. Dependent Variable: Jockey is a Saboteur = 1. | | | | | | | |
| Predictor |  |  |  | *p* | No. of obs. |  | Hosmer–Lemeshow |
| Distance to winner | −0.1266843 | 0. 0140731 | 0.8810118 | 0.000 | 14,824 | 0.0514 | *P*=0.000 |

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| Table 13. Logistic Regression Analysis. Dependent Variable: Jockey is a Saboteur = 1. | | | | | | | |
| Predictor |  |  |  | *p* | No. of obs. |  | Hosmer–Lemeshow |
| Distance to winner | −0.1155852 | 0.0154883 | 0.8908446 | 0.000 | 10,440 | 0.0434 | *P*=0.000 |

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| Table 14. Logistic Regression Analysis. Dependent Variable: Jockey is a Saboteur = 1. | | | | | | | |
| Predictor |  |  |  | *p* | No. of obs. |  | Hosmer–Lemeshow |
| Distance to winner | −0.1665207 | 0.0348909 | 0.8466053 | 0.000 | 4384 | 0.0767 | *P*=0.849 |

This suggests that the more competitive jockeys participate in acts of interference. There may be a need to reconsider leveling the playing field, as this adjustment may increase a destructive effort on the part of the players.

Does interference help? Should the jockey interfere? The next hypothesis tested these questions.

H1: Winning jockeys will participate more in sabotage than regular jockeys.

A logit regression was run on an indicator variable equaling 1 if the horse won the race and 0 if otherwise against an indicator equaling 1 if the jockey interfered and 0 if otherwise; the result showed significance (, *p* = 0.000). The control variables — the number of runners, the horses’ official rating, and the dummy variable if it was a handicap race — were added, and the results were found to be robust (, *p* = 0.000).

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| Table 15. Logistic Regression Analysis. Dependent Variable: Jockey Won the Race = 1. | | | | | | | |
| Predictor |  |  |  | *p* | No. of obs. |  | Hosmer–Lemeshow |
| Jockey interfered | 1.128535 | 0.135435 | 3.091124 | 0.000 | 15,206 | 0.0056 | *P*=0.000 |

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| Table 16. Logistic Regression Analysis. Dependent Variable: Jockey Won the Race = 1. | | | | | | | |
| Predictor |  |  |  | *p* | No. of obs. |  | Hosmer–Lemeshow |
| Jockey interfered | 1.086553 | 0.1376304 | 2.964039 | 0.000 | 15,206 | 0.0297 | *P*=0.4760 |
| Handicap | −0.2084771 | 0.0655103 | 0.8118196 | 0.001 |  |  |  |
| No. of runners | −0.1127765 | 0.0083172 | 0.8933503 | 0.000 |  |  |  |
| Official rating | 0.0043915 | 0.0008336 | 1.004401 | 0.000 |  |  |  |

To investigate further and also to ensure that the results were not influenced by the longshot bias (Griffith 1949), where better performing horses are underrated and weaker horses are overrated, a dependent variable was regressed: the performance of a horse against a dummy variable, had the jockey interfered.

For this hypothesis, a measure suggested by Brown and Chowdhury (2014) was again used:

Performance = (predicted finishing position − actual finishing position)/number of

runners in class

The predicted finishing position is a derivative of a horse’s odds in a race. Shorter odds indicate expectations for a higher ranking horse. Horses with long odds are expected to finish last. This measure is by nature an order of scale (shortest odds are predicted to finish first, second shortest to finish second, and so forth). A positive performance signals a horse succeeding beyond expectations, while a negative result means the horse has underperformed.

Regression resulted in significance (*F*1,15204 = 28.37, *p* = 0.00), meaning that the jockey who interfered had an improved performance. The average number of runners is 10.66 and the coefficient is 0.092, which means that an interferer improved their position with respect to expectations by 0.98 on average.

The odds for each jockey were added as a control variable in the following regression (*F*2,15203 = 30.88, *p* = 0.000).

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| Table 17. Logistic Regression Analysis. Dependent Variable: Performance. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Jockey interfered | 0.0920632 | 0. 017283 | 0.000 | 15,206 | 0.0019 |

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| Table 18. Logistic Regression Analysis. Dependent Variable: Performance. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Jockey interfered | 0.0877881 | 0. 0172812 | 0.000 | 15,206 | 0.0040 |
| Odds | −0.0005406 | 0.0000936 | 0.000 |  |  |

Changes in performance were also measured related to sabotage in handicap races only (*F*1,10717 = 22.81, *p* = 0.000), adding the odds as a control variable repeated with significance (*F*2,10716 = 28.66, *p* = 0.000) and followed by the same procedure for non-handicap racing, resulted in (*F*1,4485 = 4.72, *p* = 0.0299) and (*F*2,4484 = 7.73, *p* = 0.000), respectively.

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| Table 19. Logistic Regression Analysis. Dependent Variable: Performance in Handicapped Race. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Jockey interfered | 0.0958935 | 0.0200783 | 0.000 | 15,206 | 0.0021 |

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| Table 20. Logistic Regression Analysis. Dependent Variable: Performance in Handicap race. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Jockey interfered | 0.0877881 | 0. 0172812 | 0.000 | 10,719 | 0.0053 |
| Odds | −0.0009962 | 0.0001698 | 0.000 |  |  |

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| Table 21. Logistic Regression Analysis. Dependent Variable: Performance in Non-Handicapped Race. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Jockey interfered | 0.0761857 | 0.0350693 | 0.030 | 4487 | 0.0299 |

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| Table 22. Logistic Regression Analysis. Dependent variable: Performance in Handicapped Race. | | | | | |
| Predictor |  |  | *p* | No. of obs. |  |
| Jockey interfered | 0.0706668 | 0.0350718 | 0.044 | 4487 | 0.0034 |
| Odds | −0.0003421 | 0.0001044 | 0.001 |  |  |

According to the BHA, about 450 professional jockeys are listed in the United Kingdom. Data describing top U.K. jockeys for 2019 offered one more perspective, in addition to the existing literature, that allowed the times a top jockey participated in an act of sabotage on average over a long period to be counted and compared with data for regular jockeys.

H1: Top successful jockeys participate in destructive behavior (i.e., sabotage) more than regular jockeys.

A simple *t*-test checking for the top 5% of professional flat jockeys in the United Kingdom revealed significant differences between the group of the top 5% and other jockeys.

The average number of interference incidents for top flat jockeys between 01/01/2019 and 13/07/2019 was 2.86 (Table 23), which is 4.386 times the average (0.652) for the rest of the jockeys who interfered (*t* = 7.1432, *p* = 0.00). Smaller differences were observed with the jump jockeys: the top 5% of jump jockeys interfered 0.272 times on average in that period, and regular jump jockeys interfered 0.144 times on average. The test revealed weak significance (*t* = 1.2942, *p* = 0.0984).

Table 23.

|  |  |  |
| --- | --- | --- |
|  | Top flat jockeys | Regular flat jockeys |
| Average number of interference incidents | 2.863636 | 0.6528662 |
| *P*-value | 0.000 | |
|  | Top jump jockeys | Regular jump jockeys |
| Average number of interference incidents | 0. 2727273 | 0. 1449275 |
| *P-*value | 0.0984 | |

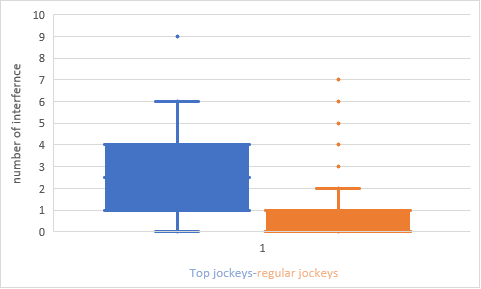


Figure 2.

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# General Discussion

Handicapping is a common tool used in contests in an attempt to reduce a priori differences between contestants and lead to an increase in aggregate effort. As noted in this paper, it has been shown in previous research that a handicap policy can indeed increase the probability of winning for weaker contestants. Drawing on the work of Brown and Chowdhury (2014), I have also demonstrated how competitive closeness is positively correlated with cases of sabotage. From data on horse racing, it has been verified that the tighter the race, the more chances for interference between jockeys and that cases of sabotage will usually occur at the top of a race between the leading jockeys.

One addition to the existing literature in this paper, is the ability to distinguish between the negative behavior (sabotage incidents) of top contestants and that of regular contestants. Using the top 5% of jockeys in the United Kingdom as representing superior contestants, I have shown that the top 5% will participate in sabotage incidents at 4.5 times the rate of regular contestants.

A number of questions arise. Is negative behavior a tactic to get to the top? Or is it that successful contestants just participate more in cases of sabotage? These questions are not answered in the scope of this paper, although they are worthwhile to consider, perhaps by separating leading jockeys into a smaller group of contestants rather than by handicapping them in an attempt to make their winning probabilities better align with those of weaker players. This is not to promote the importance of handicapping as a tool used by the contest designer for the benefits it provides, but rather, to enhance our understanding and perhaps better address the weaknesses that come with handicapping.

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# Appendix A:

Regression



Regression



Regression



Regression





Table A1.



Regression 5





Regression 6



Regression



Regression



Regression



Regression



Regression



Regression



Regression



Regression



Regression



Regression



Regression



Regression 20



