

# **Takedowns and Submissions**

The economics and decision making of  
professional mixed martial artists

*Senior Honors Thesis for the Department of Economics  
Marcell Babai*

## **Abstract**

I examine the incentives of professional mixed martial artists and how they influence the strategies of the fighters in high profile competitions. Using data collected from hundreds of professional fights, I examine the effects of 1<sup>st</sup> and 2<sup>nd</sup> round performance together on 3<sup>rd</sup> round performance and on risky behavior, in bouts lasting three rounds. Using probability logistic regressions to calculate performance, and linear regressions to estimate risk taking, we find that 1<sup>st</sup> and 2<sup>nd</sup> round performance together have little effect on third round performance. However, a good (bad) performance in the first 2 rounds reduces (increases) risk-taking behavior in the third round or changes in risk-taking behavior in the 3<sup>rd</sup> round, relative to the first two rounds. We also examine the rare cases of rematches, and find that while performance in the original fight is a good predictor of the outcome and performance in a rematch, the actual outcome of the original fight is not. That is to say that fighters who did well, but lost (by bad luck) in the original match are more likely to win the second match.

## **Acknowledgements**

I would like to thank Fight-metric for allowing us to use the data used in this thesis free of charge for the purposes of research. I would like to thank Professor Edward Kutsoati for agreeing to be my advisor on such short notice, to Professor David Garman for agreeing to be part of my thesis committee, also on such short notice, and to both of them for being so helpful throughout this endeavor. I would like to thank Professor Jeffrey Zabel for teaching the seminar class and suggesting to use the purse data even after I had thought it would have been insufficient. I would like to thank Professor Yannis Ioannides for being my major advisor and helping me with the process of beginning my thesis. Lastly, I would like to thank all those who attended my thesis defense: Andrew Sugaya, Dan Kiss, Meth Bandara, Shreya Ishita, Professor Ioannides, and my thesis committee members; Professor Kutsoati and Professor Garman. Thank you.

## Table of Contents

<b>Abstract.....</b>	<b>ii</b>
<b>Acknowledgements.....</b>	<b>iii</b>
<b>Introduction.....</b>	<b>1</b>
<b>Professional Mixed Martial Arts: A Background.....</b>	<b>2</b>
<b>Why Study Mixed Martial Arts.....</b>	<b>5</b>
<b>Sports Economics: A Brief Literature Review.....</b>	<b>7</b>
<b>Hypothesis Development.....</b>	<b>10</b>
<b>Data Description.....</b>	<b>13</b>
<b>Empirical Strategy.....</b>	<b>17</b>
<b>Hypothesis 1.....</b>	<b>20</b>
<b>Hypothesis 2.....</b>	<b>26</b>
<b>Hypothesis 3.....</b>	<b>30</b>
<b>Limitations.....</b>	<b>33</b>
<b>Results.....</b>	<b>34</b>
<b>Results 1.....</b>	<b>34</b>
<b>Results 2.....</b>	<b>37</b>
<b>Results 3.....</b>	<b>40</b>
<b>Discussion and Concluding Remarks.....</b>	<b>43</b>
<b>Tables / Graphs.....</b>	<b>46</b>
<b>Bibliography.....</b>	<b>48</b>

## Introduction

Mixed martial arts (MMA) is one of the fastest growing sports today. Inspired by ancient Greek Pankration (no rules fights), an organization called the Ultimate Fighting Championship (UFC) invited martial artists of various styles for an open tournament with virtually no rules. Since its conception in 1993, the competitions have evolved into a sport with many safety rules and regulations, including boxing style rounds, and has spread across the world, picking up popularity especially in Japan, China, Brazil and America through other organizations. As time has gone on, the martial arts generally used in the sport have been distilled to three major skill sets: Kick boxing, wrestling, and Brazilian JiuJitsu (BJJ) or “submission grappling.” Any match can be won in one of three ways: By knock out (KO) or technical knockout (TKO) (34.8% of fights), by submission (30.4%), or by judges scoring card at the end of all the rounds (34.7%), with the remainder being draws and disqualifications.

While some safety rules have changed the sport in very obvious ways (like no eye gouging, headbutting, hair pulling, etc.), other rule changes have had more subtle influences on the incentives of the fighters. Rules, like the judges scoring system done over three, 5 minute rounds, may change how the fighters choose to pace themselves. Since rounds are judged individually, fighters now can choose when to exert effort in order to maximize chances of winning a fight. However, a knockout or submission will always win the fight regardless of the standing in the rounds. This presents the fighters with interesting risk assessment situations.

All of these complications to a fight beg the question; what are the fighters doing when they step into the octagon? That is to say; when we talk about what makes a “good” fighter, what does that really mean? How do the specific situations dictate what a fighter should be doing to win? In this essay, we will be examining how the incentives fighters face create a discrepancy between how we think fighters should act, and how they actually act.

## **Professional Mixed Martial Arts: A Background**

In the first UFC tournament, held in 1993, the fights were truly barbaric. There were no rounds, and fighters had only cups on as protective gear. No strikes or techniques were prohibited, though some led to a fine (a strike to the opponent's groin would incur a fine that the striker would have to pay to the victim of the blow). The event was in tournament form with three direct elimination rounds, meaning a fighter could potentially fight three of these brutal fights in one night, and would have to continue regardless of the injuries sustained in the previous fight (e.g. missing teeth). In some cases there were replacement fighters who could step in, but then the fighter would forgo a large sum of money to the substitute. Also, since such a tournament had never been held before (at least, not of such high profile), fighters rarely knew what to expect when entering the cage.

The sport has come a long way since then. These days the fighters wear protective gloves and a mouth guard; the fighters are split into weight classes, which vary by organization; and the fight is broken into three 5 minute rounds (five if it's a championship fight). Also, fighters tend to fight a maximum of only three or four times a year, as opposed to several in a single night. Such rules are similar to those of MMA's predecessor, boxing. Unlike boxing though, the sport is currently dominated by one organization, the Ultimate Fighting Championship or UFC, owned by Zuffa LC. This monopoly power allows them to have much stronger negotiating power in contracts with the fighters that the promoters of boxing matches did. This is very important to take into account when analyzing the incentives of the fighters, since it is not the same as what boxers faced in the past.

Also unlike boxing, the rules of engagement are completely different. In MMA, combatants are allowed to use virtually any fighting technique at all, including, but not limited to: punching, elbowing, kicking, kneeing, armlocks, leg-locks, chokes, strangles, spine-locks and any variety of tackles and slams. The fights can continue with combatants standing or wrestling on the ground. Most professional

fighters have several coaches, each for a different aspect of the sport. Usually fighters are said to have clear strengths and weaknesses in their abilities, which are split up into two main groups: “stand-up game” and “ground game,” (with much more detailed subdivisions as well). These skill sets will be important for our later analysis.

The round system is very similar to that of traditional boxing. Each of the rounds is judged by three judges. A 10 is given to the fighter that the judged deemed winner of the round, and a 9 to the loser (or, rarely, an 8 if it was a dominant victory). Points can be taken away for breach of rules as well. At the end of the allotted rounds for the fight, if no fighter has won by submission or by the referee's stoppage, the fight is decided by the total number of points awarded by the three judges. A referee is told to stop the fight if a fighter is no longer “intelligently defending himself” (known as a technical knockout: TKO), or if a fighter is unconscious (KO). In the case of a submission hold or overwhelming onslaught of strikes, a fighter may give up the fight by tapping the ground or his opponent three times. Illegal techniques include but are not limited to: Headbutting, eye gouging, biting, hair pulling, small joint manipulation, kicking downed opponents in the head, and striking the base of the skull.

Also unlike boxing, the payment system for the fighters is very different. In boxing, fighters are paid before the fights a prearranged amount (called the purse). In MMA, within the UFC, fighters agree upon a purse and an additional bonus for winning. On top of that, they have a chance of getting special bonuses depending on their performance in relation to others fighting that night. Of the 16 fighters that fight each night (8 fights), 2 are awarded the “fight of the night” bonus, 1 (potentially) is awarded the “knockout of the night” bonus, and 1 (potentially) is awarded the “submission of the night” bonus, all of which are equal for any given evening. These bonuses usually range from \$35,000 to \$80,000 (they have tended rise as time goes on), and are completely independent of the purse that the fighter receives. The bonuses that fighters get for winning a fight are usually double that of the purse, but there are many exceptions that have a completely different contract agreements (often times sacrificing a win

bonus for a larger purse).

There are differences in rules across organizations. Some organizations (like those in Japan) allow for kicks to the head of a downed opponent, but do not allow elbows at all. Some have different systems for rounds, and scoring; with a typical variation being that there is only one long round. However, for the purposes of our analysis, we will be looking only at fights that are scheduled for 3 rounds.



## **Why study mixed martial arts?**

The study of mixed martial arts from a economics perspective has many benefits that may not immediately be apparent to economists. Sports economics is a growing field, often times with surprising results. These results have some significance for greater economic study that is unique to sports economics and may be difficult to find in other areas of study. Due to its controlled environment, sports gives us the unique opportunity to test theories in an incentive based system with relatively little noise due to outside forces. These results could have great potential to be used as a teaching tool, especially for young up-and-coming economists who are familiar and interested in the sports. Lastly, many sports are often a major part of our lives, and spending time studying the sports under a new lens could be very insightful just for its own sake.

Similar to a lab experiment, in many ways professional sporting events are a controlled environment in which the participants act. However, it retains the real world aspect of having individual people making real decisions in their natural environment without thinking that they are in an experiment. In the example of mixed martial arts fighters, we know their incentives, their history, and can easily collect data since so much is recorded for television. This allows the studies to be specific, and still retain some power to the results, due to its real-world nature. Also, for theoretical purposes, sports provide a unique set of rules and incentives that may not be found in the “real world” otherwise. This presents us with new and interesting experiments that come up naturally. In the case of MMA, a new sport rising in popularity, this is a great opportunity to be one of the first people to study the game.

These results have the potential to be great tools for teaching. Often times a parable or contrived example is used to teach specific principles of economic theory. It is rare that a testable , real-world application of equilibrium strategies in game theory exists in its pure form. Studying sports may

allow us to find exemplary cases that make understanding principles easier for students, especially if the students are interested in the sports.

As a final reason, sports are interesting for their own sake. People spend a lot of time doing and watching sports, so it is fair to say that sports play an important part of many people's lives. If that is the case, then it stands to reason that we should take a critical look at the underlying principles of the sport that may elude the look of the average fan or participant. Unlike amateur athletes, since the livelihood of the players depends on how well they maximize their profit, we are likely to see optimal strategies executed by the participants.

The study of the economics and incentives of professional mixed martial artists is not just a fleeting interest. There are many justifiable reasons to study it as a sport, and specifically to study MMA. As a combat sport, if MMA strategies are studied, it may have potential practical applications for self-defense. Regardless of its practicality, MMA is a new and yet unstudied sport with a goldmine of potential areas of study, especially with regard to its differences with boxing, which has already been studied to some extent. It would be a shame to waste this opportunity to study the brand new field that is MMA.

## **Sports Economics: A brief Literature Review**

With regard to the study of this sport, only medical and health studies have been conducted, and nothing has been written from an economic perspective. There is much dispute on the actual health and physical risks involved, especially when compared with boxing. These effects are beyond the scope of this thesis. Here we will focus on how economic theory might predict behavior of the fighters. In this section I will discuss what research has already been done that would relate to similar research in MMA.

Due to the youth of the sport of mixed martial arts, there has been virtually no research done related to the sport. The closest related topic that has been researched is professional boxing. While the sports are different in many key ways, looking at past research on boxing will give some insight into how to view MMA. Furthermore, other sports in certain perspectives, are also similar to MMA in a way that gives meaning to discussion, i.e. tennis, Sumo, or other individual one-on-one sports. While payment is very different in these cases, risk assessment, payoffs, and strategies may be analogous when using game theory analysis.

We can start with the theoretical work of Tenorio (2000)<sup>i</sup>, which addresses that the purse of the fighter is determined before a fight, causing incentive problems with regard to effort. Tenorio argues that consumption-smoothing considerations, in light of savings, are not a strong enough incentive for fighters gaining large purses to put in maximum effort before a fight, thus presenting a moral hazard. This is in part allowed by the “casual” fan who is willing to watch a fight regardless of past performance of the boxer, practically forgiving the boxer for a bad fight. More theoretical work was done by Amegashie and Kutsoati (2005)<sup>ii</sup> on boxers' effort in relation to rematching. Amegashie and Kutsoati make the case that, given nearly equal levels of ability of the fighters, a higher chance of a rematch will result in higher aggregate effort exerted by the fighters, in comparison to the case where

the chance of a rematch depends on aggregate effort. Moreover, these results are not solely applicable to boxing, but other sporting events (like tennis), and for our purposes MMA.

With regard to moral hazard, due to the fact that there is one dominant promotional company for MMA (as opposed to several in boxing), this issue is less of a problem in MMA. Since there is only one main promotional company with strong monopoly power, they have the most leverage when making contracts. This allows them to have the pay for fighters depend on performance without the fighters being able to find a better contract elsewhere. This results in much lower pay for the fighters, with the top fighters making roughly a quarter million per fight as opposed to several million made by top professional boxers. More importantly for our purposes, since pay goes up (or at least has a chance to go up) with performance, we do not face much of a moral hazard in MMA.

Regarding strategies and effectiveness, the work of Romer (2002)<sup>iii</sup> addresses fourth downs in professional American football. Romer uses dynamic programming to estimate the value of the ball at specific locations on the field, then compares these valuations with the possible outcomes and payoffs of common plays or kicks. These outcomes are used to calculate expected payoffs of different strategies. It is quite possible that similar techniques could be used to assess strategies in MMA, most specifically in the ground game aspect of the sport where the positions and choice of actions are distinct and easy to measure. However, such analysis may be beyond the scope of this paper due to insufficient data.

Relating to fan satisfaction and its connection to athlete performance, Gonzalez-Gomez and Picazo-Tadeo (2009)<sup>iv</sup> wrote about soccer fans' satisfaction with a team. To evaluate satisfaction, they use the standard measure of comparing expectations of the fans for the team at the beginning of the season to the actual result of the team at the end of the season. A similar measure could be used for MMA fans' satisfaction.

Continuing with soccer, Palacios-Huerta (2003)<sup>v</sup> wrote about the implications of Minimax

theorem on soccer penalty kicks. Palacios-Huerta modeled the kicks as a zero-sum simultaneous game of complete information. He observed that the players' strategies were nearly exactly what would have been predicted by the Nash Equilibrium. The stress of this work is that these predictions hold true so accurately, because the livelihood of the players depends on profit maximizing performance, similar to our professional MMA fighters.

In another paper by Apestequia and Palacios-Huerta (2010)<sup>vi</sup>, the soccer penalty kicks are further studied. This time they examine how psychological pressure can influence the performance of the players. In this case too, they use evidence from actual soccer games, which makes it a randomized natural experiment. When a match ends in a draw, teams alternate taking penalty kicks to determine victory. They find that teams who are randomly chosen to kick first in a tie situation, win about 60% of the time – which the authors attribute to psychological pressures – as opposed to the 50% that would be expected if there were no psychological pressure on the players.

Returning to combat sports, Duggan and Levitt's (2000)<sup>vii</sup> essay on the highest ranked Sumo wrestlers focuses specifically on the incentives that the Sumo face, and how they pick their strategies. Specifically, the paper is with regard to intentionally losing, and trading a current loss for a future win. The trade is made by Sumo who have already won the necessary number of bouts, with other Sumo who are “on the bubble,” or require still one more fight to remain in the highest ranks (and preserve their higher pay). The authors cite the non-linearity of the payoffs to be the cause of this behavior. A very similar type of logic will be used for the purposes of the current essay, making that the most relevant work to this thesis.

## Hypothesis Development

Before examining the data, I would like to discuss the motivation for this research and the hypotheses I wish to test. As mentioned in the literature review, sports can have issues where incentives of the athletes lead to optimal strategies that do not properly align with the way in which the fans would want or expect the athletes to behave. Over the years it has come to my attention that such a discrepancy exists in the yet unexamined sport of mixed martial arts.

The issue, in short, is the problem that fights become boring once one of the fighters has gained a decisive advantage in the eyes of the judges. No longer needing to prove himself, the fighter will not try as hard, and will perform worse in the last round given that he has won the first two, which is boring for the viewers. Since winning the first two rounds out of three has ensured victory for the fighter, he has no incentive to fight at his best for the third round. Since exerting less effort has benefits of comfort for the fighter, and trying hard has the cost of potential injury and discomfort, the fighter would try less hard, and his performance would drop in the third round. This leads us to hypothesis 1:

*Hypothesis 1: A fighter who performed well in the first two rounds would have a drop in performance for the third round.*

Even if performance does not drop in the third round, since good fighters would tend to do well in all rounds, we may be able to measure a change in strategy specifically for situations in which winning the current round no longer has benefits for a fighter. We can think of this change in strategy as a change in risk.

Once a fighter has won the first two rounds, no longer needing to prove himself, he takes less risk. This immediately implies that the fighters did in fact take risks in the fight before this advantage was gained. So, from where does this risk stem? Any martial artist of even beginner level skill would be able to inform us that any offensive technique attempted has some inherent risk to the fighter, since

any offensive technique lowers one's defenses for at least a short period of time.

While inactivity (A defensive strategy) may be risk-less, it has a continuous cost to the fighter, which is that the judges will give the fighter fewer points, and an opportunity cost of not gaining potential points by attacking. However, these costs are no longer costs once a fighter has won the first two rounds (of a three round fight), since he has already guaranteed a victory in the eyes of the judges assuming he survives (is not knocked out or submitted) until the end of the fight, and no longer needs to acquire points.

Since the benefits to attacking also include a potential early end to a fight (a knockout or submission before the end of the third round is an automatic victory), the cost of attacking for the other fighter, who has lost the first two rounds, goes down, since part of the risk of a counterattack goes away. The fighter has already “lost on points” (meaning that if the fight goes to the judges, the fighter will lose), so he no longer takes into account the points lost when he is hit successfully. This change in risk, in clear terms states that a fighter who has already won two rounds will now take on a defensive strategy, and the loser an offensive one.

This alone tells us that there will be a sharp change in the amount of risk taken in the third round, leading to hypothesis 2:

*Hypothesis 2: A fighter who performed well in the first two rounds would reduce the amount of risk taken in the third round.*

Our last hypothesis is on a different topic: rematches. While rematches are rare, it occasionally happens that two fighters, after having a fight, will face-off one (or rarely two) more times. In these situations, we can examine how the outcome of the previous fight would influence performance and risk in the following encounter.

We might imagine that fighters who had won the first fight may believe that they are simply better than their opponent, and therefore not prepare as much for the rematch, or take unnecessary risk.

Conversely, the loser of the original fight knows just how difficult the first fight was, will train harder, and be more careful with risk. Both of these intuitions would suggest that the second fight would be the opposite story of the first. This brings us to hypothesis 3:

*Hypothesis 3: A fighter who won the first fight will tend to lose the rematch, underperform, and take more risk.*

In the following sections we will examine the validity of these hypotheses.



## Data Description

Data for this thesis was provided by Fightmetric<sup>viii</sup>, a company that has been aggregating data on past fights, and is continuing gather data. This data is typically used by sports commentators and sports magazines for a fee.

I received the datasets on October 29<sup>th</sup> 2010, at which point, there were 3171 fights in the dataset. There were a total of 7 datasets, split up by relevance (by round, by fight, by fighter, by event, etc), which I aggregated into one large dataset that uniquely identifies a fighter and his fight (FightFighterID) for each observation. For each fighter, in each fight, the data includes how many of what technique was attempted (and how many landed) by each fighter each round. Some of the data is incomplete, and after imposing limitations for specific regressions, the number of observations drops drastically at times from the total 6210 originally in the data.

Table 1: Summary statistics for fight data

Variable	Obs	Mean	Std. Dev.	Min	Med	Max
Strikes Landed	4650	19.91	20.3	0	14	153
Strikes Attempted	4650	47.62	50.3	0	32	421
Takedowns Attempted	4650	2.37	3.41	0	1	30
Takedowns Landed	4650	1.04	1.69	0	0	16
Submissions	4650	0.61	1.11	0	0	10
R1Strikes Landed	4650	10.27	9.7	0	8	94
R1Strikes Attempted	4650	23.66	20.65	0	19	180
R1Takedowns Attempted	4650	1.21	1.65	0	1	13
R1Takedowns Landed	4650	0.55	0.85	0	0	8
R1Submissions Attempted	4650	0.38	0.79	0	0	8
R2Strikes Landed	2510	10.24	8.71	0	8	98
R2Strikes Attempted	2510	24.92	20.19	0	20	211
R2Takedowns Attempted	2510	1.17	1.52	0	1	12
R2Takedowns Landed	2510	0.51	0.81	0	0	5
R2Submissions Attempted	2510	0.25	0.6	0	0	5
R3Strikes Landed	1590	10.71	8.92	0	9	60
R3Strikes Attempted	1590	27.21	22.08	0	21	143
R3Takedowns Attempted	1590	1.35	1.7	0	1	12
R3Takedowns Landed	1590	0.56	0.86	0	0	6
R3Submissions Attempted	1590	0.26	0.59	0	0	6

While specific strike techniques may be of interest, for our purposes, what matters is simply the

aggregate number in a fight and a round of those attempted and successful. In addition to strike techniques, the other large deciding factor for fighter is the number of takedowns in a fight. The summary statistics for strikes and takedowns are as follows: (See table 1, “Summary statistics for fight data”)

While these variables are very important, there is clearly a lot of information missing here, which unfortunately is not available in our dataset. First, we do not know what strike technique is used, and we have now even lost the information of the target of the strike (head, body, or leg). Second, we do not know how much force was in the hit, which would be extremely difficult data to collect. Regardless, from this data we can calculate a few important statistics relevant to the fights. These would include accuracy (the ratio of techniques landed and techniques attempted) as well as a ratio between how many of a technique one fighter landed successfully compared to his opponent. In addition to these, we can also calculate the number of strikes evaded by a fighter (either by dodging or blocking) by taking 1 minus the Accuracy of his opponent. These are summarized here: (See Table 2: “Summary Statistics for Performance Evaluations”).

Table 2: Summary Statistics for Performance Evaluations

Variable	Obs	Mean	Std. Dev.	Min	Med	Max
Accuracy	1198	42.25	15.19	0	41.32	100
Takedown (TD) Accuracy	943	45.93	34.86	0	46.67	100
Strike Ratio In	1186	0	0.96	-3.83	0	3.83
Strikes Evaded %	1198	57.75	15.19	0	58.68	100
R1Accuracy	1195	43.44	19.86	0	41.67	100
R1TDAccuracy	717	49.88	40.43	0	50	100
R1Strike Ratio In	1146	0	1.07	-3.85	0	3.85
R1Strikes Evaded %	1195	56.56	19.86	0	58.33	100
R2Accuracy	1171	42.04	18.84	0	40	100
R2TDAccuracy	710	48.8	41.11	0	50	100
R2Strike Ratio In	1114	0	1.09	-3.53	0	3.53
R2Strikes Evaded %	1171	57.96	18.84	0	60	100
R3Accuracy	1155	40.74	18.25	0	40	100
R3TDAccuracy	704	46.14	39.91	0	50	100
R3Strike Ratio In	1086	0	1.13	-3.47	0	3.47
R3Strikes Evaded %	1155	59.26	18.25	0	60	100

A few things to note about the number of observations should be clarified at this point. The observations used in the table above are only the ones in fights that were scheduled for three 5 minute rounds, and did not end prematurely (due to knockout or submission). This must be done to understand what happens in a fight that will be determined by the judges' score cards. We could include data about fights that ended early, but such information would be misleading, giving much lower numbers, since less time is spend fighting.

In addition to the data received from FightMetric.com, we were also given access to the purses of the fighters from the Nevada Athletic Commission. However, this dataset was very small and incomplete, and we could not use it to find any meaningful results.

Many of the variables listed above could be influenced by physical attributes of the fighters. Included in my data set was the height, reach (wingspan), date of birth, and weight class of the fighters. Fighters are split into discrete weight classes as follows: heavyweight (under 265 pounds), Light heavyweight (under 205), Middleweight (under 185), Welterweight (under 170), Lightweight (under 155)

It is important to check which, if any, of these variables are correlated. The following is a table of the correlation coefficients of the key variables that we will use later in our regression analysis: Table 3; “Physical attribute and Performance Metrics Correlation Summary”. As can be seen in the table, none of the physical attributes are highly correlated with any of the key variables or each other (except for reach and height, which is expected).

Table 3; “Physical attribute and Performance Metrics Correlation Summary

	Accuracy	TDAcc	Str.Ratio	Evaded%	Height	Reach	Age	Hvy	Lhvy	Mdl	Wtr	Lwt
Accuracy	1											
TDAccuracy	0.25	1										
Strike Ratio In	0.52	0.34	1									
Strikes Evaded %	-0.16	0.11	0.46	1								
Height	0.13	0.06	0.04	-0.16	1							
Reach	0.13	0.06	0.04	-0.14	<b>0.84</b>	1						
Age	0.04	-0.06	-0.08	-0.05	0.05	0.04	1					
Hvy	0.08	0.03	-0.02	-0.07	0.38	0.35	0.1	1				
Lhvy	-0.05	0.01	0	0.04	0.33	0.31	0.16	-0.1	1			
Mdl	0.07	-0.05	-0.01	-0.1	0.28	0.21	0.09	-0.12	-0.16	1		
Wtr	0.12	0.06	0.02	-0.1	0.06	0.08	-0.08	-0.16	-0.21	-0.24	1	
Lwt	-0.09	-0.04	-0.01	0.08	-0.41	-0.32	-0.17	-0.17	-0.23	-0.26	-0.35	1

## Empirical Strategy

To begin to understand how to create a model of the choices that fighters make in a fight, it is first necessary to get an understanding of how the fighters should act as dictated by most practicing martial artists. Knowing how the fighters approach the game and the traditional thought on how the fights are scored will give us insight as to how to create models of the outcomes of their strategies.

The judging of the fights is mostly subjective, but they follow specific guidelines. The main criteria for fighters include clean strikes, effective grappling, octagon control, and aggression. The more strikes landed and the more powerful the strikes, the more the judge would favor that fighter. Effective grappling consists of taking down the opponent and remaining in dominant position. Octagon control and aggression is comprised of initiating attacks and stepping towards your opponent, not away. However, these are only the judges way of scoring the fight. We must remember that a submission or knockout will also end the fight. This distinction gives us insight into the thought process of the fighters. Depending on what they are pursuing (winning by decision or by early ending), they may have different strategies. Let us examine the actions that they would attempt to get closer to a victory, and see what the costs and benefits are.

Some actions' benefits are obvious, but should be stated anyway. All strikes landed by a fighter are good both in the eyes of the judges, and with two additional benefits: potential for a knockout, and inflicting pain on the opponent (depending on the strength and accuracy of the strike) will generally lead to a reduced ability to retaliate later in the fight. Wrestling an opponent to the ground (a takedown) has similar benefits: Gaining a dominant position for more powerful strikes, for potential submissions, and defense from the same things against you, as well as points in the eyes of the judges. Lastly, a submission attempt has the benefit of potentially ending the fight in the moment, if successful. It is important to note for later that submissions are, for all practical purposes, attempted only from

positions on the ground.

Those were only the benefits, but each action has a cost as well. Each strike attempted can leave the attacker open to either a counter strike, or a takedown. This is a risk that the fighters know they take every time they attempt a strike. In addition to the risk taken, after attempting several strikes the fighter will have expended energy, leading to fatigue. That same is true for a takedown attempt. Each attempt (especially a failed one) requires lots of energy, opens him up to counter strikes, and even has an added risk of landing him in a bad position on the ground opening him up to submission attempts. Lastly submission attempts have the same risks of taxing the fighter's stamina, but also, if they fail, they tend to land the fighter in a weak position on the ground. These risks are difficult to calculate directly, since we don't have time stamped data, and can't tell what happened in the seconds following a successful or failed technique attempt.

The one thing we can measure, however, is performance. We can tell if a fighter has won or lost, and observe what kinds of patterns fit with a winning fighter. Once we can establish what patterns are indicative of higher probability of winning, we can use that as an evaluation of performance. Then we can track performance throughout a fight, and see how it might change. Once we can do this we could ask very simple question based on incentives.

In any given fight, it may be difficult to quantify the “score” of a fight, especially due to knockouts and submissions which allow a fighter to win even if he has been losing most of the fight. However, fights are scored by the judges between rounds. Unfortunately, my data does not include the round by round scoring of the judges. This is not much of an issue when taking into account the fighters' behavior choices within a fight, since they don't receive these scores until the end of the match. Each fighter can asses his own performance within each round, and judge whether or not they believe they have won that round. This is not very difficult, as evidenced by the fact that disputes of scores are extremely rare.

First I would like to investigate what kinds of patterns lead to a higher probability of winning.

We started with the linear regression for winning:

$$Win = B0 + B1*TakedownsLanded + B2*StrikeRatioLN + B3*StrikesLanded + e$$

Where *TakedownsLanded* is the total number of takedowns landed in the fight, *StrikeRatioLN* is the natural log of the ratio of strikes of the fighter and his opponent, and *StrikesLanded* is the total number of strikes landed in the fighter by the fight. In this regressions, we are using aggregated data from the entire fight, not round by round data. Also, since we are interested in the point score of the judges, and how they might influence the fighters, we focus our interest only on fights that do not end early by knockout or submission. This tends to reduce the magnitude of the error terms, since a win by knockout or submission could occur even when all other performance valuations have pointed towards an advantage for the other fighter for most of the fight. That is to say, even a poor fighter can have a major comeback just by throwing one winning punch, which would throw off the estimation of good performance by this regression.

However, since the values given by this regression are not all between 0 and 1, the results are difficult to interpret. Thus, a probability logistic regression model would be more fitting, since a win is defined as a binary variable (1 for a win, and 0 for a loss – draws were few, and eliminated from the data set).

$$prob(Win) = A1*TakedownsLanded + A2*StrikeRatioLN + A3*StrikesLanded + e$$

We will call this predicted probability value “performance.”

$$Performance = A1*TakedownsLanded + A2*StrikeRatioLN + A3*StrikesLanded$$

## Hypothesis 1

The next step is to ask a question to which economic analysis could provide insight. A common issue that fight fans address is boring fights, especially by top fighters who just want to make sure that they win, without trying hard. This leads to boring fights, especially in the later rounds of combat, once a lead has been taken by the dominant fighter (*hypothesis 1*). Common sense might tell us that good fighters should always perform well, but a critical eye with economic analysis may shed some light on what is actually happening. First we must ask if this anecdotal evidence supported statistically, and then we will attempt to answer why or why not, through an economic lens.

The common sense theory states that after having won a decisive lead in points (by winning more than half the rounds) a fighter has little incentive to do anything more than survive for the last round. While there are some incentives to do so: winning a special bonus, building a reputation, etc., simply winning clearly benefits one's career, bank account, and reputation, and may be worth more than the expected payoff of attempting a spectacular victory. Also, given that the risks required to attempt getting a special bonus are high, and the potential gains of building a reputation are hard to estimate, any risk averse fighter would opt for the safe choice, and simply win the fight, assuming he is in the position to do so.

This brings us to our hypothesis: A fighter who has performed well in the first two rounds (of a three round fight) will perform worse in the third (*hypothesis 1*). More specifically, the fighter will be less aggressive and more defensive. We can observe this in the variable for performance in each round, as well as each individual metric used to calculate performance, within the round. Looking at each individual metric may be more meaningful, since the values for performance by round are calculated by using the coefficients generated by the probit function, and applying them to the round by round data. Since some of the metrics (Strikes landed and takedowns landed) are cumulative over the duration of the match, these performance levels will be artificially low, and the values cannot be interpreted the



way that the performance for the whole fight can be, as a probability of victory. However, as relative measures, they are still meaningful, and can generally be interpreted as a probability of winning the round. So we use the same coefficients as in our previous regression, but this time apply it to round by round data:

$$R1Performance = A1*R1TakedownsLanded + A2*R1StrikeRatioLN + A3*R1StrikesLanded$$

This would be repeated for each round. We will be looking at how high performance in the first two rounds of a three round match predict the performance in the third round. We use the linear regression:

$$R3Performance = B0 + B1*R1Performance + B2*R2Performance + B3*R12Performance + B4*ReachPercentage + B5*HeightPercentage + B6*Age + B7*Heavyweight + B8*LightHeavyweight + B9*Middleweight + B10*Welterweight + B11*Lightweight + e$$

Where, R12Performance is the interaction term (product) between the first and second round. Here we will control for other factors that may affect behavior overall. Reach and height percentage are values calculated as the the percentage difference of height and reach from the mean of the fighters in the weight-class. The weight-class variables are binary dummy variables to see if weight-class itself may affect behavior. Age is the age of the fighter at the time of the event.

At this point we must first examine the correlation coefficients to see if there is an issue of collinearity (Table 4. “Correlation Coefficients of Dependent Variables”). The correlation coefficients tell us something obvious; simply that fighters' performance tends to be consistent over the rounds. However, there are clearly exceptions to this, which is why we want to examine the discrepancy in the

effects of any single round and the effects of two rounds together. While we do have some collinearity, it is not strong enough to prevent us from continuing with our analysis.

Table 4. Correlation Coefficients of Dependent Variables  
R1Performance R2Performance R12Performance

R1Performance	1		
R2Performance	0.47	1	
R12Performance	0.79	0.82	1

Here we are looking for non-linearity. What we hope to gain from this regression is an understanding of how performance in previous rounds would predict performance in later rounds. More specifically, the difference between doing well in one of the first two rounds, and doing well in both, and how they affect strategic decisions in the third round. To do this, at this point we will have to limit our results to fights that are scheduled for 3 rounds, and that made it to the third round of the fight – that is, they didn't end earlier in rounds 1 or 2 by KO or submission.

Due to the fact that a fighter must win only two of the three rounds of a match, economic theory would state that, given that a fighter has won the first two rounds, his payoff for winning the third would be relatively small, and he would not try as hard to win, since risk (of losing the entire fight by knockout or submission) must be taken to increase the chances of victory in any round. This means that there is a non-linear payoff function for victories in each round. Given that a fighter has lost the first round, the second and third rounds have much higher payoffs, since both must be won if the fighter is to have a chance at winning the bout. Given that a fighter has lost both the first and second rounds, he stands to gain only from a knockout or submission, which means he would no longer care to do techniques that only impress the judges, but would focus on techniques that have the highest chance of ending the fight early.

To gain a clearer understanding of the details of the implications of this non-linearity on the behavior of the fighters, we will look at the specific metrics used in calculating the performance

variable for the 3<sup>rd</sup> round individually. Before we look at a linear regressions, it may help to get a better understanding of what might be happening here through a table of summary statistics, as we change round 1 and round 2 performance, and see how that changes the mean of round 3 metrics. See table 5: “Summary of key variables with changes in Round 1 and 2 performance.”

Table 5: Summary of key variables with changes in Round 1 and 2 performance  
**For Fights lasting three rounds that do not end prematurely**

Variable	Obs	Mean	Std. Dev.	Min	Max
R1Performance	1146	0.56	0.32	2.23E-006	1
R2Performance	1114	0.55	0.33	0	1

Variable	Obs	Mean	Std. Dev.	Min	Max
R3Performance	1308	0.55	0.34	0	1
R3Strikes Landed	1426	10.71	8.95	0	60
R3Strike Ratio In	1308	0	1.2	-3.47	3.47
R3Takedowns Landed	1426	0.58	0.87	0	6

**(With no conditions imposed)**

Variable	Obs	Mean	Std. Dev.	Min	Max
R3Performance	322	0.76	0.26	0	1
R3Strikes Landed	350	14.61	9.68	0	60
R3Strike Ratio In	322	0.69	1.05	-3	3.47
R3Takedowns Landed	350	0.93	1.07	0	6

**(When R1Performance and R2Performance are greater than .65)**

Variable	Obs	Mean	Std. Dev.	Min	Max
R3Performance	190	0.31	0.28	0	1
R3Strikes Landed	203	7.85	6.33	0	32
R3Strike Ratio In	190	-0.75	0.99	-3.47	2.4
R3Takedowns Landed	203	0.3	0.6	0	3

**(When R1Performance and R2Performance are less than .40)**

While that can give us some intuitive insight into how the variables relate to each other, and the results don't surprise us. Round 3 performance metrics seem to go up as round 1 and 2 performance goes up. However, this doesn't tell us anything about the rates at which these variables change in relation to each other. We would need a linear regression to better understand what happens when round 1 and 2 performance move together, and its effects on round 3 performance metrics. Using the same template as before, we get the following linear regression models:

$$R3TakedownsLanded = B0 + B1*R1Performance + B2*R2Performance + B3*R12Performance + B4*ReachPercentage + B5*HeightPercentage + B6*Age + B7*Heavyweight + B8*LightHeavyweight + B9*Middleweight + B10*Welterweight + B11*Lightweight + e$$

AND:

$$R3StrikeRatioLN = B0 + B1*R1Performance + B2*R2Performance + B3*R12Performance + B4*ReachPercentage + B5*HeightPercentage + B6*Age + B7*Heavyweight + B8*LightHeavyweight + B9*Middleweight + B10*Welterweight + B11*Lightweight + e$$

AND:

$$R3StrikesLanded = B0 + B1*R1Performance + B2*R2Performance + B3*R12Performance + B4*ReachPercentage + B5*HeightPercentage + B6*Age + B7*Heavyweight + B8*LightHeavyweight + B9*Middleweight + B10*Welterweight + B11*Lightweight + e$$

This lets us differentiate between different aspects of performance that may change depending on past round performance. This way we can see what parts of strategy are affected by a high probability of winning previous rounds (as indicated by performance). We can be more specific with our regression, using relative values instead of absolute ones. We can run the same regressions, but this time with the difference between round 3 performance and the average of round 1 and 2 performance.

This yields the regressions:

$$\Delta Performance = B0 + B1*R1Performance + B2*R2Performance + B3*R12Performance + B4*ReachPercentage + B5*HeightPercentage + B6*Age + B7*Heavyweight + B8*LightHeavyweight + B9*Middleweight + B10*Welterweight + B11*Lightweight + e$$

AND:

$$\Delta Takedowns = B0 + B1 * R1Performance + B2 * R2Performance + B3 * R12Performance$$

$$B4 * ReachPercentage + B5 * HeightPercentage + B6 * Age + B7 * Heavyweight +$$

$$B8 * LightHeavyweight + B9 * Middleweight + B10 * Welterweight + B11 * Lightweight + e$$

AND:

$$\Delta StrikeRatioLN = B0 + B1 * R1Performance + B2 * R2Performance + B3 * R12Performance$$

$$B4 * ReachPercentage + B5 * HeightPercentage + B6 * Age + B7 * Heavyweight +$$

$$B8 * LightHeavyweight + B9 * Middleweight + B10 * Welterweight + B11 * Lightweight + e$$

AND:

$$\Delta StrikesLanded = B0 + B1 * R1Performance + B2 * R2Performance + B3 * R12Performance + e$$

$$B4 * ReachPercentage + B5 * HeightPercentage + B6 * Age + B7 * Heavyweight +$$

$$B8 * LightHeavyweight + B9 * Middleweight + B10 * Welterweight + B11 * Lightweight + e$$

These regressions make more sense, because what we are looking for is a change in strategy over the course of the fight relative to earlier performance in that fight. We will look at the results of these regressions and their predictive power in the results section.

## Hypothesis 2

What we notice when doing the previous analysis is that we cannot glean much information about 3<sup>rd</sup> round performance solely judging from 1<sup>st</sup> and 2<sup>nd</sup> round performance (as discussed in the results section). Initially this would seem to contradict the economic theory that states that performance should decrease given that the fighter has already won the first two rounds. However, there may be a flaw in the approach to the question. While we may believe that performance would go down, we aren't taking into account that fighters who performed well in the first two rounds would continue to do so in the third. Also, that performance may be affected by endurance and skill whereas the theory should be making a prediction about strategy, which relates to choices, not output.

Take the simple case of looking at takedowns landed. While we would assume that a risk averse fighter would execute fewer takedowns and as a result land fewer takedowns, we're measuring the wrong variable. Takedowns landed is a good measure of performance, but not of strategy. We should be looking at the choices fighters are making, which is what techniques they attempt, not what they land. A fighter doesn't choose to land a technique, he chooses to attempt one. This would produce a formula for calculating risk as such:

$$\text{Risk} = C1 * \text{StrikesAttempted} + C2 * \text{TakedownsAttempted} + C3 * \text{SubmissionsAttempted}$$

This would be a good measure of risk, but it does not take into account some basic principles that martial artists' common sense would inform us of. A somewhat more complex model that takes into account skill level would be necessary. In other words, a takedown is not as risky of a move if the fighter is highly skilled at executing a takedown. This raises the issue of how to calculate skill. There may be many complicated and involved ways of estimating skill, but we will settle for a simple one that we can work with for now.

The accuracy of a technique is not a good enough measure of skill, because it does not take into account the evasive skills of the opponent. Therefore we will take a weighted average of a fighter's

accuracy with a technique multiplied by the average evasive accuracy of his opponent over all of the opponent's matches. This gives us the formula:

$$\text{TechniqueSkill} = \text{AccuracyVS1} * \text{AvgEvasive1} + \text{AccuracyVS2} * \text{AvgEvasive2} + \dots$$

We can do this for both of the techniques we are studying: strikes and takedowns. We could do the same for submissions, but since most submissions fail we would end up getting a value of zero for submission skill too often, which would be meaningless in our next formula for risk:

$$\text{TechniqueRisk} = (\text{OpponentEvasionSkill} * \text{Attempts}) / \text{TechniqueSkill}$$

Which gives us overall risk as:

$$\text{Risk} = C1 * \text{StrikeRisk} + C2 * \text{TakedownRisk} + C3 * \text{SubmissionAttempts}$$

Table 6: Summary statistics for Risk

Variable	Obs	Mean	Std. Dev.	Min	Max
Risk	3290	38.32	33.76	0	417.48
R1Risk	3290	32.92	29.79	0	406.3
R2Risk	2049	31.56	27.63	0	425.71
R3Risk	1369	33.56	29.1	0	427.96

This same evaluation can also be used for round by round risk taking, by simply taking the number of techniques attempted in that round instead of the aggregate. We can take a quick look at the summary statistics for risk and see how it might move with performance in earlier rounds (See Table 6: “Summary statistics for Risk”). Using this new metric, we will try a similar regression, but this time with risk as the dependent variable.

$$\begin{aligned} R3Risk = & D0 + D1 * R1Performance + D2 * R2Performance + D3 * R12Performance + \\ & D4 * ReachPercentage + D5 * HeightPercentage + D6 * Age + D7 * Heavyweight + \\ & D8 * LightHeavyweight + D9 * Middleweight + D10 * Welterweight + D11 * Lightweight + e \end{aligned}$$

(We use the same control variables as in regression 1.)

Table 7: Summary of changes in risk with changes in Round 1 and 2 performance

Variable	Obs	Mean	Std. Dev.	Min	Max
DeltaRisk1	1214	<u>0.18</u>	1.27	-1	17.5
DeltaRisk2	1212	<u>0.14</u>	1.01	-1	18.65
DeltaRisk12	1212	<u>0.08</u>	0.72	-1	9.37
<b>(With no conditions imposed)</b>					
Variable	Obs	Mean	Std. Dev.	Min	Max
DeltaRisk1	229	<u>0.24</u>	1.98	-0.91	17.5
DeltaRisk2	229	<u>-0.02</u>	0.59	-0.91	4.33
DeltaRisk12	229	<u>0.01</u>	0.67	-0.91	4.58
<b>(When R1Performance and R2Performance are greater than .8)</b>					
Variable	Obs	Mean	Std. Dev.	Min	Max
DeltaRisk1	140	<u>0.16</u>	0.94	-1	5.03
DeltaRisk2	140	<u>0.16</u>	0.78	-1	2.79
DeltaRisk12	140	<u>0.12</u>	0.74	-1	3.73
<b>(When R1Performance and R2Performance are less than .3)</b>					

More important than the absolute value of the risk in the 3<sup>rd</sup> round, we can look at the relative value of risk in the 3<sup>rd</sup> round when compared to the first, the second, and the geometric mean of the first and second. Like before, we will examine how the means of the change in risk differ as the value of performance in the first two rounds changes (See Table 7: “Summary of changes in risk with changes in Round 1 and 2 performance”). As can be seen from the tables, the mean of the change in risk is greater if the fighters did poorly in the first two rounds, and is less if they did well. This supports the hypothesis that fighters would reduce their risk if they have done well in the first two rounds, and vice versa (*hypothesis 2*). To further explore this hypothesis we take the following three regressions in addition to our first one:

$$\Delta Risk1 = D0 + D1 * R1Performance + D2 * R2Performance + D3 * R12Performance + D4 * ReachPercentage + D5 * HeightPercentage + D6 * Age + D7 * Heavyweight + D8 * LightHeavyweight + D9 * Middleweight + D10 * Welterweight + D11 * Lightweight + e$$

AND:



$$\Delta Risk2 = D0 + D1*RIPerformance + D2*R2Performance + D3*R12Performance + \\ D4*ReachPercentage + D5*HeightPercentage + D6*Age + D7*Heavyweight + \\ D8*LightHeavyweight + D9*Middleweight + D10*Welterweight + D11*Lightweight + e$$

AND:

$$\Delta Risk12 = D0 + D1*RIPerformance + D2*R2Performance + D3*R12Performance + \\ D4*ReachPercentage + D5*HeightPercentage + D6*Age + D7*Heavyweight + \\ D8*LightHeavyweight + D9*Middleweight + D10*Welterweight + D11*Lightweight + e$$

Here we control for the same factors as before, but this time we focus on how risk taking strategy has changed through the rounds, as affected by performance in the first two rounds as the focus. In this case  $\Delta Risk1$  is the difference between 3<sup>rd</sup> and 1<sup>st</sup> round risk,  $\Delta Risk2$  between the 3<sup>rd</sup> and 1<sup>st</sup> and  $\Delta Risk12$  between the 3<sup>rd</sup> and the average of the 1<sup>st</sup> and 2<sup>nd</sup> rounds.

If economic theory holds true, and the fighters are using optimal efficiently strategies, then we would expect risk to go down as first and second round performance are higher, and vice versa: risk should go up if first and second round performance were poor. This is because the potential benefits of these risky strategies goes down, since if the fighters have already won the fight in the eyes of the judges. They may potentially get a spectacular finish, which would build reputation and maybe even get them a bonus, but these benefits are less tangible than the immediate reward for winning the fight. On the other side, if a fighter has lost the first two rounds, he stands to gain nothing from being risk averse: He is currently losing the fight and can only win by knockout or submission. Even with a loss, a spectacular fight could get him fight of the night bonus, and build his reputation in spite of a loss. By examining the above regressions, we will see if this is, in fact, how the fighters behave.

### Hypothesis 3

For this hypothesis, we examine rematches between fighters. First, we must understand that rematch fights are not random. There is usually a specific reason to have a rematch, relating to the fact that the audience perceived the outcome of the first fight was somehow flawed. They may have thought that the winner was lucky, the decision by the judges was poor, that the fight was too close, or one of several other reasons. Due to this fact, it is important to examine what kinds of fights lead to rematches, giving us insight into how the second fight may turn out.

Table 13: Correlation coefficients relating to rematches

Variable	Win	Performance	PreWin	PrePerformance
Win	1			
Performance	0.77	1		
PreWin	0.06	0.06	1	
PrePerformance	0.29	0.39	0.47	1

Looking at table 13, we see that PrePerformance (the performance of the original fight) and PreWin (the binary outcome of the first fight) have a smaller correlation coefficient than Performance and Win of a typical fight (non-rematch). This tells us that there may be a misalignment of performance and outcome that leads to the rematch. Maybe viewers believe that the winner “stole” the victory in some way, and that he did not actually deserve the victory.

Table 14: Means of Performance in Rematches, given outcome of first match

Variable	Obs	Mean	Std. Dev.	Min	Max
$\Delta$ Performance	157	<u>0.01</u>	0.37	-0.87	0.98
<b>Average, without conditions imposed</b>					
$\Delta$ Performance	77	<u>0.15</u>	0.33	-0.76	0.98
<b>If the last fight was lost</b>					
$\Delta$ Performance	76	<u>-0.12</u>	0.37	-0.87	0.76
<b>If the last fight was won</b>					

However, this leads to a situation where the loser of the first fight still needs to prove himself.

This may lead us to think that the first fighter will perform better in the second fight, since they fear confirming the suspicions of the viewers. This seems to be supported by comparing average performance of fighters in rematches, and rematches when one fighter has lost or won (See table 14).

While this lends support to it, a rather simply regression analysis can give us further insight into this phenomenon. We examine the probability regression model:

$$\begin{aligned} Prob(Win) = & E1*PreWin + E2*PrePerformance + E3*ReachPercentage + E4*HeightPercentage + \\ & E5*Age + E6*Heavyweight + E7*LightHeavyweight + E8*Middleweight + E9*Welterweight \\ & + E10*Lightweight + E11*PreEndEarly + e \end{aligned}$$

As well as the linear regressions:

$$\begin{aligned} Performance = & E0 + E1*PreWin + E2*PrePerformance + E3*ReachPercentage + \\ & E4*HeightPercentage + E5*Age + E6*Heavyweight + E7*LightHeavyweight + \\ & E8*Middleweight + E9*Welterweight + E10*Lightweight + E11*PreEndEarly + e \end{aligned}$$

AND:

$$\begin{aligned} \Delta Performance = & E0 + E1*PreWin + E2*PrePerformance + E3*ReachPercentage + \\ & E4*HeightPercentage + E5*Age + E6*Heavyweight + E7*LightHeavyweight + \\ & E8*Middleweight + E9*Welterweight + E10*Lightweight + E11*PreEndEarly + e \end{aligned}$$

AND:

$$\begin{aligned} \Delta Risk = & E0 + E1*PreWin + E2*PrePerformance + E3*ReachPercentage + E4*HeightPercentage + \\ & E5*Age + E6*Heavyweight + E7*LightHeavyweight + E8*Middleweight + E9*Welterweight \\ & + E10*Lightweight + E11*PreEndEarly + e \end{aligned}$$

Where the prefix “pre” indicates a metric taken from the original fight, and  $\Delta$  indicates a change

from the original fight. We also are check for the effects of how the last fight ended (PreEndEarly) to see if a knockout or submission in the first fight would change the strategies of the fighters. Most specifically we would like to see if this would change risky behavior, since classical martial arts theory would teach us that knockouts and submissions tend to come about when a fighter takes too much risk. Again we control for the same factors as in previous regressions. We will look at the results of these regressions in the results section.

## **Limitations**

When presented with the massive dataset that was given to us by Fightmetric, we faced the daunting task of choosing what question we wanted to ask given the data. Originally, I planned on using the data in combination with the purse data supplied by the NAC to see how the potential bonuses would have affected risky behavior in fighters in the octagon. However, this posed several problems; the first of which was insufficient purse data. We therefore could not use this to get any conclusive results relating to the purses. Though it was sufficient enough to be used as a control variable in our second regression, we can see that it reduced the dataset by too much to be useful by itself.

The second, is the lack of detail in the data. A few important pieces of information that would help us in producing more results would include: time-stamped data, position in which techniques were attempted, specific techniques used, etc. This may have made our risk assessment more accurate. Given the level of information we have, this is extremely difficult. Generally, when practitioners are asked what kinds of behavior would be deemed risky, the answers revolve around very specific techniques (which are not recorded in the data, since all strikes are simply counted as strikes), very specific strategies of when to use those techniques (also not recorded due to lack of time stamps), or using specific strategies and techniques when they match up poorly with the given opponent (i.e. trying to wrestle with the best MMA wrestler – which would require a “skill” metric, not given in the data).

While the limitations on the purse data have been prohibitive, using our simple calculations on risk do lend us some insight into the behavior of the professional fighters. That said, further study with more detailed and complete data could give much greater insight into the actual behavior of the fighters.

## Results

Taking the regressions we used to evaluate performance, the coefficient generated are shown in Table 8: “Predicting Performance using the probit regression on victories.” Since this is a probability logistic regression, the coefficients can be interpreted such that one additional unit of the independent variable adds that much probability to the chance of victory. Again, what is important is not the actual values of the coefficients, but their relative magnitudes. Since these values are taken from fights that went to a judges score card, these values can roughly be interpreted as the relative value assigned to each element of a fighter by the judges.

Table 8: Predicting Performance using the probit regression on victories

VARIABLES	Win
TakedownsLanded	0.0882***
StrikeRatioLN	0.476***
StrikesLanded	0.00287***
Observations	1456

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

### **Results 1**

Using these same relative valuations of elements of performance, we will next calculate the perceived performance valuations of fighter round by round, as well as the interaction term between the first and second round. See Table 9: “Results of Hypothesis #1, Regression 1” with the variable of interest in bold.

What we find, not surprisingly, is that round 1 and round 2 performance separately are positively correlated with round 3 performance. This is expected, simply because fighters that do well in the first two rounds are likely to be good fighters, better than their opponents and likely to continue to do well in the third round.

We do, on the other hand, see what may be surprising. We only notice a statistically significant negative coefficient on the R12Performance variable when the dependent variable is round 3 strikes landed. While this regression would have predicted that R12Performance would have a negative coefficient when predicting round 3 performance across the board, this is not what we find. It appears that this regression has relatively weak predictive power, as evidenced by poor statistical significance on most of the variables of interest.

Table 9: Results of Hypothesis #1, Regression 1

VARIABLES	R3Perf	R3StrikeR	R3TDLanded	R3StrikesL	R3Accuracy	R3Subs Att	R3Strikes Att
<b>R1Performance</b>	<b>0.170***</b>	<b>0.427**</b>	<b>0.23</b>	<b>5.073***</b>	<b>-0.63</b>	<b>-0.04</b>	<b>15.64***</b>
<b>R2Performance</b>	<b>0.483***</b>	<b>1.438***</b>	<b>0.287*</b>	<b>10.93***</b>	<b>11.59***</b>	<b>0.18</b>	<b>20.96***</b>
<b>R12Performance</b>	<b>0</b>	<b>0.2</b>	<b>0.31</b>	<b>-5.561*</b>	<b>2.8</b>	<b>-0.2</b>	<b>-18.84**</b>
FighterAge	-0.00596**	-0.0206**	-0.0166**	0.01	-0.248*	-0.0122**	0.14
HeightPerc	0.01	0.0279*	-0.0588***	0.382***	0.2	0	0.891**
ReachPerc	-0.00647*	-0.0225*	0.01	-0.295***	-0.15	0.01	-0.677**
Hvy	0.03	0.16	-0.236*	1.71	3.84	-0.08	-1.94
LHvy	0.02	0.07	-0.14	2.05	-1.78	-0.157*	3.41
Mdl	0.01	0.06	-0.16	-0.24	6.039***	-0.03	-6.359**
Wtr	0.01	0.05	-0.217**	1.68	3.39	-0.01	-0.4
Lwt	0	-0.01	-0.01	0.77	2.33	-0.02	-0.9
StrikeSkill	0	0	0	0.02	0.514***	0.00631***	-0.339***
TDSkill	0.00101*	0	0.0137***	-0.0353**	0.03	0	-0.0998**
Observations	885	885	936	936	930	936	936
R-squared	0.32	0.3	0.19	0.11	0.19	0.04	0.09

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

One might argue that such a regression that seems to indicate decrease in performance may be attributed to fatigue, since a fighter could experience greater fatigue with greater performance earlier in a fight. A fighter who landed many strikes in both the first and second round, would be too tired to land so many in the third round, and has burned himself out. However, even this might be strategic pacing by the fighter. Knowing that a decisive victory in the first two rounds would lead to an easy third round, the fighter chose to expend all his energy in the first two rounds. This kind of relationship

between rounds would be difficult to perceive in the regression. While this may be the fighter's intent on beginning the fight, it isn't actually influenced by their performance in the first two rounds, but his effort in them. Since we cannot measure effort, we cannot determine if this type of strategy is being used. Later we will see if we can find a way to eliminate fatigue from the picture.

One of our regressions, predicting strikes landed in the third round, does have a statistically significant negative coefficient on R12Performance. This probably has the simplest explanation, just that the fighter no longer even attempts to land as many strikes, since each one opens up a chance for getting hit in return. In fact, since this is most likely the cause of the reduced number of strikes landed, we can actually test the strikes attempted regression as well (appended onto the end of Table 9).

We see that this is even more statistically significant and greater in magnitude than the coefficient for the regression on strikes landed. This is a clear indicator that fighters are making a conscious choice to attempt fewer strikes given that they've done well in the first two rounds. While this may be attributed to fatigue, remember that fatigue would affect the losing fighter as well, but we find that their number of strikes attempted goes up, and they should be more tired since they've been struck more times.

Now that we understand the meaning of the signs of the coefficients, the next step is to interpret the magnitudes of the coefficient. We can calculate the elasticity of strikes attempted by measuring a change in terms of standard deviations from the mean of dependent variables, when there is a standard deviation change in the independent variables. This gives the following results for the variables of interest whose coefficients were statistically significant:

Variable	Elasticity of R12Performance
Strikes Attempted	-0.28
Strikes Landed	-0.2



Here we can see that the elasticities are rather high, and that this effect is important. In other words, there is significant non-linearity in the regressions. The aggressive strategies associated with high performance in the first two rounds drops significantly for the third round, given that a fighter has done well in the first two rounds, and conversely given that a fighter has done poorly in the first two rounds, his performance will make up for it by being significantly more aggressive in the third round.

This regression also had a second part where it was the changes in the performance that were measured as opposed to their absolute values. The results of these regressions gives us little new insight, seeing as it tells almost the same story as this earlier regression. The regression is summarized in Table 10: “Results of Hypothesis #1, Regression2.”

Table 10: Results of Hypothesis #1, Regression2

VARIABLES	$\Delta$ Perf12	$\Delta$ StrLanded12	$\Delta$ StrAttempted12	$\Delta$ StrRatLN12	$\Delta$ TDL12	$\Delta$ Accu12	$\Delta$ Subs12
<b>R1Performance</b>	<b>-0.330***</b>	<b>-2.38</b>	<b>-0.06</b>	<b>-1.011***</b>	<b>-0.22</b>	<b>-7.927**</b>	<b>-0.08</b>
<b>R2Performance</b>	<b>-0.02</b>	<b>3.527**</b>	<b>5.11</b>	<b>-0.06</b>	<b>0.28</b>	<b>3.5</b>	<b>0.1</b>
<b>R12Performance</b>	<b>0</b>	<b>-7.195***</b>	<b>-13.01**</b>	<b>0.07</b>	<b>-0.1</b>	<b>-1.37</b>	<b>0.06</b>
FighterAge	-0.00596**	-0.04	0.12	-0.0234***	-0.01	-0.307**	-0.0125**
HeightPerc	0.01	0.306**	0.613**	0.0257*	-0.0321***	0.38	-0.01
ReachPerc	-0.00647*	-0.224**	-0.522**	-0.0231*	0	-0.17	0.01
Hvy	0.03	1.35	1.46	0.14	-0.18	0.19	-0.02
LHvy	0.02	0.6	0.07	0.1	-0.231**	0.93	-0.03
Mdl	0.01	-0.21	-2.82	0.07	-0.15	3.896*	-0.09
Wtr	0.01	0.66	0.02	0.07	-0.221**	1.76	-0.06
Lwt	0	0.31	-0.5	0.02	-0.01	2.32	-0.1
StrikeSkill	0	0.01	0	0	0	-0.01	0.00403*
TDSkill	0.00101*	0.0307*	0.02	0	0	0.103***	0
Observations	885	936	936	885	936	930	936
R-squared	0.13	0.08	0.04	0.1	0.03	0.04	0.02

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## Results 2

However, these results alone are telling us something about performance, not strategy. The regression with strikes attempted in the 3<sup>rd</sup> round as the dependent variable gives us a hint as to where these models should really be going. Examining attempted techniques is by far the better way to

understand strategical choices made by fighters. For a table of the regressions with risk and changes in risk as the dependent variables as dictated by the second regression, again controlling for the same factors as in regression 1, see Table 11: “Results of Hypothesis #2, Regression 1.”

Table 11: Results of Hypothesis #2, Regression 1

VARIABLES	R3Risk	ΔRisk1	ΔRisk2	ΔRisk12
<b>R1Performan</b>	<b>11.34</b>	<b>-0.26</b>	<b>0.578***</b>	<b>0.03</b>
<b>R2Performan</b>	<b>24.52***</b>	<b>1.065***</b>	<b>-0.258*</b>	<b>0.241**</b>
<b>R12Performa</b>	<b>-23.49**</b>	<b>-1.032***</b>	<b>-0.618***</b>	<b>-0.511***</b>
ReachPerc	-0.832*	-0.02	-0.01	-0.01
HeightPerc	0.43	0.0392***	0.01	0.0211**
FighterAge	-0.49	0	0	0
Hvy	-5.25	0.02	0.09	0.02
LHvy	4.64	0.01	-0.1	-0.04
Mdl	-8.121*	-0.12	-0.1	-0.11
Wtr	-4.54	0.12	-0.07	0.01
Lwt	-0.19	-0.02	-0.1	-0.07
Observations	809	809	809	809
R-squared	0.04	0.11	0.08	0.04

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 12: Results of Hypothesis #2, Regression 2

	R3RiskP	ΔRisk1P	ΔRisk2P	ΔRisk12P
<b>R1Performance</b>	<b>34.83**</b>	<b>0.2</b>	<b>1.899***</b>	<b>0.736**</b>
<b>R2Performance</b>	<b>31.06*</b>	<b>1.397***</b>	<b>0.19</b>	<b>0.51</b>
<b>R12Performance</b>	<b>-45.00*</b>	<b>-1.596**</b>	<b>-2.143***</b>	<b>-1.268**</b>
ReachPerc	-2.405**	-0.04	-0.0599*	-0.0499**
HeightPerc	1.1	0	0.0843**	0.04
FighterAge	1.22	-0.02	0.03	0.01
LHvy	-18.56	0.16	-0.62	-0.22
Mdl	-16.97	0.07	-0.822***	-0.345*
Wtr	-7.47	0	-0.27	-0.12
Lwt	-2.65	0.13	-0.572*	-0.18
Purse	0.02	0	0	0
Observations	104	104	104	104
R-squared	0.17	0.15	0.32	0.15

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

While the dataset I have collected on the purses of fighters is very small, we can redo the regressions with purse as a control factor. Remember this is the amount of money (in thousands of US

dollars) that is guaranteed to the fighters regardless of the outcome of the fights. While the purse seems to have little effect on the change in risk taken, when we control for the purse, we get amplified magnitudes for the effects of round 1 and 2 performance. The results are summarized in Table 12: “Results of Hypothesis #2, Regression 2.”

As we can see, these regressions show the most predictive power, especially when we look at the value of round 3 risk, as well as the relative value of round 3 risk when compared to the average of round 1 and round 2 risks. Again these signs are what are mostly with what we are concerned, but interpreting the magnitudes could give us information about just how important these effects are. We can calculate the elasticities in terms of standard deviations from the mean of dependent variables, when there is a standard deviation change in the independent variables. This gives us the following tables:

Variable	Elasticity of R12Performance
Round3 Risk	-0.27
$\Delta$ Round1 Risk	-0.24
$\Delta$ Round2 Risk	-0.19
$\Delta$ Round12 Risk	-0.22

When we include the fighter's purse as a control factor:

Variable	Elasticity of R12Perf. With Purse
Round3 Risk	-0.51
$\Delta$ Round1 Risk	-0.37
$\Delta$ Round2 Risk	-0.66
$\Delta$ Round12 Risk	-0.56

Interpreting these elasticities is difficult, since units of risk, or change in risk are difficult to understand. However, even though we might not understand what this means in absolute terms we can have a sense of what these values mean in relative terms. We understand that there is some distribution

of performance in the first two rounds and some distribution of risk taken in each round. What this is saying is that a standard deviation change in the interaction term results in roughly 1/5 of a standard deviation of the change in risk for the third round. If we take into account the purses, then it would account for half of a standard deviation change in risk for the third round. This may not seem significant, but this results in fewer attempted techniques that can clearly change the outcome of the match, and how the combatants appear to be fighting in the eyes of the viewers.

### **Results 3**

Following these hypotheses, we also had our 3<sup>rd</sup> hypothesis about rematches. Looking at the results of the regressions (Table 15: Results of Hypothesis 3), we notice some surprising fact. First we notice that winning the first bout, when controlling for performance in the first match, is negatively correlated with winning the second match, performance in the second match, and change in performance between the first and second matches. However, high performance in the first match predicts better performance and higher probability of winning the second match.

This may seem surprising at first, but in truth is telling us the story of why there was a rematch to begin with. If the viewers did not feel that there was a high chance of an upset (win by the loser) in the second match, there would most likely not be one. What this means is that the basis for deciding on a rematch is done based on the discrepancy between the outcome and the performance.

In addition to this aspect, already setting up the initial loser to a high chance of victory, there is probably a psychological effect as well. The fighter who won the first fight may be overconfident going into the second fight and not prepare as well for it. This may explain the  $\Delta$ PrePerformance variable, which tells us that the winner's performance tends to drop significantly for the second fight.

Table 15: Results of Hypothesis 3

VARIABLES	$\Delta$ Win	Performance	$\Delta$ PrePerformance	$\Delta$ PreRisk
<b>PrePerformance</b>	<b>0.809***</b>	<b>0.523***</b>	<b>-0.477***</b>	<b>-13.51</b>
<b>PreWin</b>	<b>-0.264*</b>	<b>-0.129*</b>	<b>-0.129*</b>	<b>-5.7</b>
PreEndEarly	0.21	0.02	0.02	8.84
ReachPerc	0.02	0.02	0.02	-2.545*
HeightPerc	0.06	0.02	0.02	2.47
FighterAge	0.01	0	0	-0.54
Hvy	-0.14	-0.12	-0.12	9.16
LHvy	-0.02	-0.09	-0.09	-2.86
Mdl	0.02	0.02	0.02	18.98
Wtr	-0.02	0.03	0.03	16.41
Lwt	-0.04	-0.07	-0.07	6.82
Observations	85	83	83	83
R-squared		0.35	0.33	0.15

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Interestingly enough, we do not find what we would have expected with regard to risk. The fighter that lost the first fight, we might expect to be more careful, and less risky for the rematch, but the data does not support this. This could be explained by the need for the fighter to prove himself the second time around. This fighter wants to overcompensate for the initial loss by not just winning, but winning in a more decisive fashion so as not to get a label of being an “even match” for the opponent (since one win and one loss would generally lead to that assumption). This need for a decisive victory over the opponent would lead to riskier behavior for those who seek such a victory, but reduced risky behavior by those who are more concerned just by victory and not by the way in which it is achieved. As such, it is difficult to make a prediction about the risky behavior of any fighter, given his past performance. Even what we expected, that the PreEndEarly variable would influence risk, was untrue. This too would mostly likely be explainable by the fact that different fighters assess the value of different outcomes differently and with enough variance that we would not see a trend in how they react in their risky strategies.

## **Discussion and Concluding Remarks**

These results have some important implications about the sport and how the fighters deal with the incentives they face. On the one hand, we get a better understanding of the way fighters act, which is a positive analysis. On the other hand, the implications could lead to us to some possible methods of avoiding these pitfalls that reduce fan excitement and utility (caused by lower performance of the fighters), which is normative reasoning.

In essence the the switch of strategies (caused by the non-linearity of the payoff function) is a result of the fact that a fighter who has won the first two rounds has already “won” half of the fight. That is to say, he no longer needs to prove himself to the judges, but only has to worry about the early ending of the fight. Conversely, the fighter who lost the first two rounds has already lost that same half of the fight. Neither fighter cares any longer about the judges' score cards. This is a shift in the payoff function of the fighters that could be the cause of the shift in strategies. Maybe if fans begin to fully understand this concept, they will expect a boring 3<sup>rd</sup> round, and maybe they will leave the audience sooner. However, the low probability event of a knockout by the losing fighter in the 3<sup>rd</sup> round might be exciting enough for the fans as is.

However, if this low probability comeback submission or knockout victory is not exciting enough, a change must be made in the sport to keep every round more interesting. For this to happen, the payoff function should have two components to it: 1. It should not change (drastically) over the rounds (else some rounds will be more exciting than others); 2. It should always promote incentives for aggressive and exciting strategies. Due to the cash bonuses for exciting fights, the second condition is generally met throughout the fight, unless there is a sufficient change in the payoff function between rounds such that the risk involved would outweigh the potential gains of the bonuses. Thus, we would not have to worry about the second condition, given that the first one is satisfied under current rules.

The simplest solution to this would be to simply not have any rounds in which a fighter has already won by points. Granted, this would reduce the number of rounds given that a fighter wins two in a row, but that is similar to a knockout reducing the number of rounds. If the fights would be too short, then we could always increase the number of required victorious rounds to 3 instead of 2. However, this leads to potentially 5 round matches, which may be too long for most fighters to undertake with regard to their stamina. This can be done, as evidenced by the fact that championship matches are scheduled for 5 rounds. Then again, if we wish to keep a difference in fight length between championship and normal fights, then championship fighter would have to be scheduled for 7 potential rounds. If the fights were scheduled with the current 3 or 5 rounds, except with cutting the fights short in the case of a majority of victorious rounds, then we would have shorter fights, but they may be more exciting.

This is just one possible solution to the problem of non-linear payoffs for fighters. It would also eliminate some element of luck, since the worse fighter would have fewer opportunities to achieve a low probability victory. This would do a better job of ensuring that the better fighter wins the fight more often. That is to say, a smaller difference in skill would lead to a larger probability of victory when compared to the current system in which luck plays a larger role in determining the winner. While many fans may find this to be a favorable aspect of the sport, the counterargument could be made that such low probability events are exciting, and the potential to see them is what makes the sport enjoyable to spectators and should be left that way.

The sport of MMA is complex enough that relatively small adjustments in the rules, and thus the payoffs for the competitors, can have a large influence on how the sport is played. By tweaking the rules, it is possible to align the players' incentives with what the fans would want to see and expect the fights to be like.

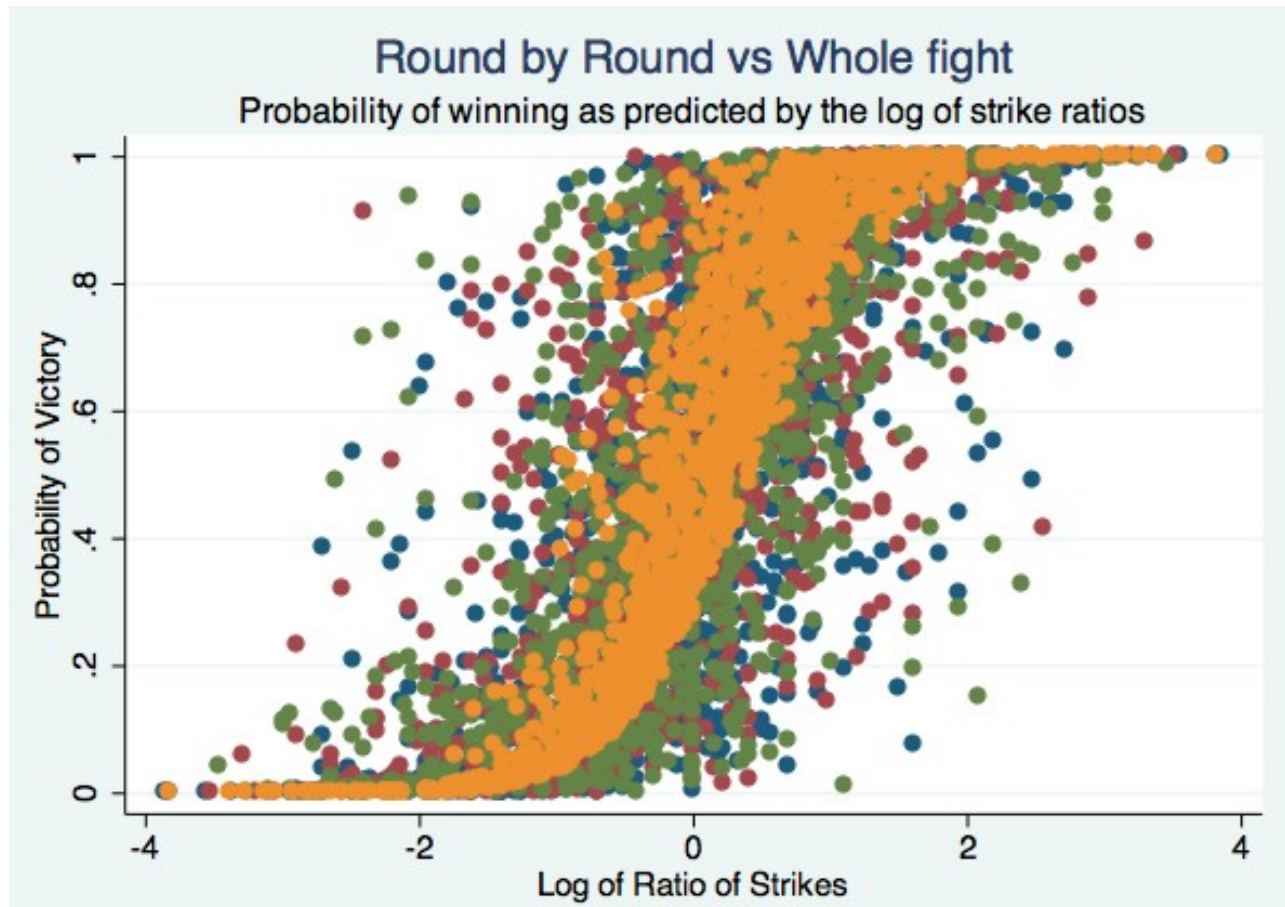
With regard to hypothesis #3, there really is nothing that could be changed by the fight

organizations to change the behavior of the fighters, nor does there need to be. If anything, the results of these regressions just give us a little predictive power for rematches. They also tell us something about the power of the “performance” metric. We notice that the performance in a previous match is a better predictor of winning the current match than the actual outcome of the match. This confirms that high performances that ended in a loss are, in fact, outliers in the data, as evidenced by the fact that these fighters tend to come back and win a disproportionate number of times.

These results are still limited in scope, and further research with more detailed and disaggregated data could potentially lead to much more interesting insights about the sport. As this is just the first research paper on professional mixed martial arts, I hope that this is just the beginning for further economics research for the sport.

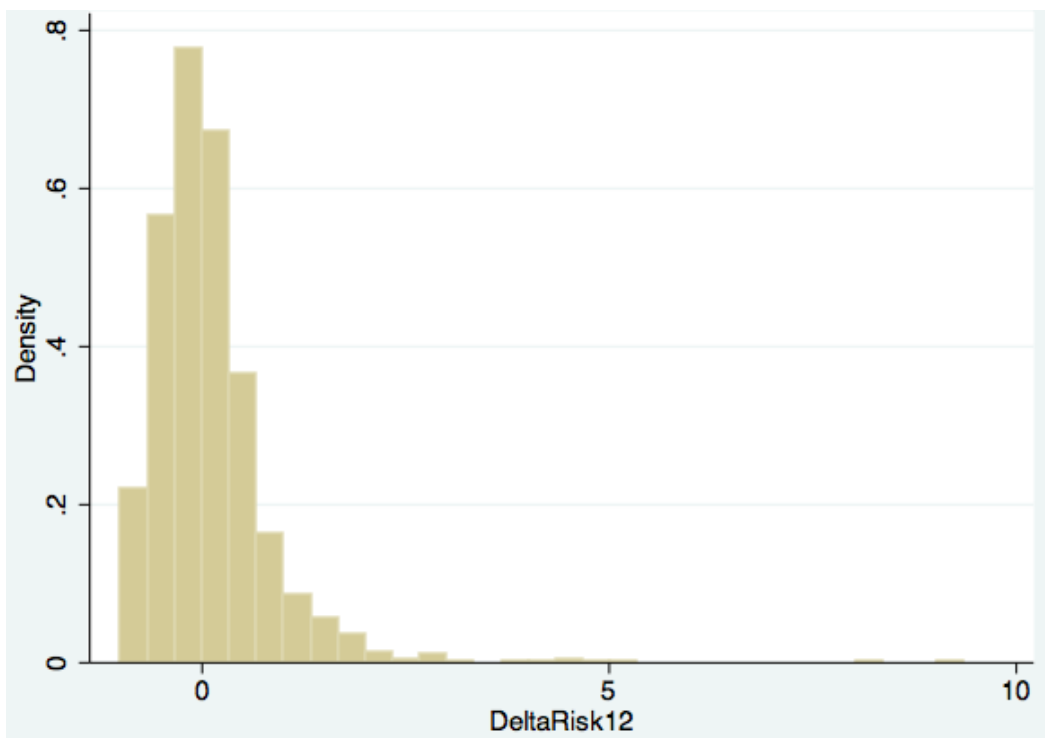
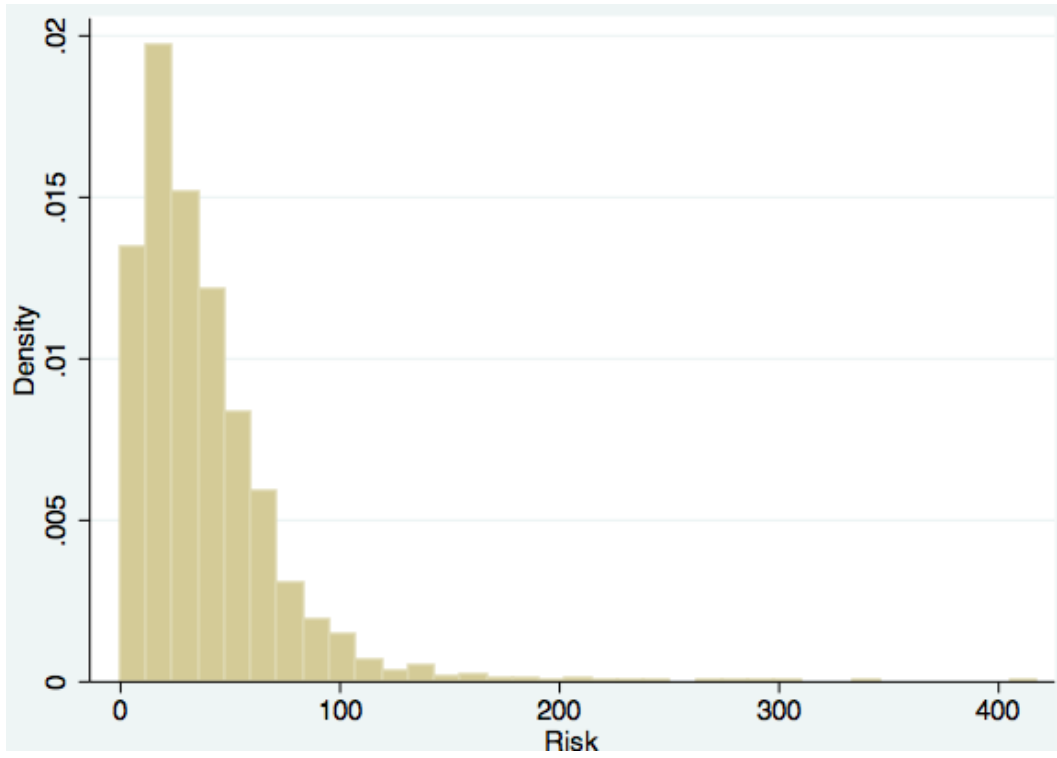


## Tables / Graphs



Blue: Round 1, Red: Round 2, Green: Round 3, Orange: Aggregate.

Distribution of risk metric, and change between 3<sup>rd</sup> and the average of 1<sup>st</sup> and 2<sup>nd</sup> round risk.



- i Tenorio, R. (2000), "The Economics of Professional Boxing Contracts," *Journal of Sports Economics* I, 2000, pp. 363-384.
- ii Amegashie, J. Atsu, and Edward Kutsoati. "Rematches in Boxing and Other Sporting Events." *Journal of Sports Economics*. 6.4 (2005): 401-411.
- iii Romer, David. "It's Fourth Down and what does the Bellman Equation Say? A Dynamic-Programming Analysis of Football Strategy." *NBER Working Paper Series*. 9024 (2002)
- iv González-Gómez, Francisco, and Andrés J. Picazo-Tadeo. "Can We be Satisfied with our Football Team? Evidence from Spanish Professional Football." *Journal of Sports Economics* (2009): Web. 15 Mar
- v Palacios-Huerta, Ignacio. "Professionals Play Minimax." *The Review of Economic Studies* 70 (2003) 395-415
- vi Apesteguía, Jose, and Ignacio Palacios-Huerta. "Psychological Pressure in Competitive Environments: Evidence from a Randomized Natural Experiment." *American Economic Review* 100 (2010)
- vii Duggan, Mark, and Steven D. Levitt. "Winning Isn't Everything: Corruption in Sumo Wrestling." *NBER Working Paper Series*. 7798 (2000)
- viii Fightmetric.com