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Who's #1? Using Regression Analysis to Rank MotoGP Riders

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MotoGP is the world's preeminent motorcycle racing tour. Historically, the ranking of competitors in this sport has been limited to the use of a cumulative summary of points earned, or championships won throughout a rider's career. The present ranking methods are flawed for numerous reasons, but chief among them are these are the methods' inability to account for the length of a rider's career, or the effects of the motorcycle he rode, in determining his spot in a list of rankings. In this paper, an ordered logistic regression is employed in an attempt to account for the influences and scenarios not considered by simpler methods of ranking. Results suggest there is some promise to using econometrics to develop more accurate rider rankings.

JEL Classification: L83, J33, C57

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Table of Contents

I. Introduction to MotoGP

The earliest iteration of the motorcycle was created in by Sylvester H. "Howard" Roper in 1868. Seen as more of a mechanical novelty for display than a viable means of transit, it consisted of a two wheel bicycle frame powered by a two cylinder, coal-fired steam engine (McCann, 1972). Nonetheless, the engineering community saw the potential of this invention, and within 20 years of its advent, more powerful gasoline powered prototypes were in development in Europe and North America (Falco, 1998).

By the dawn of the 20th century, mechanized bicycle prototypes easily defeated human competition, and with that, motorcycle production firms began to form and develop models for a consumer market. Upon their popularization, motorcycles became nearly as common as automobiles as a mode of transit. With the increasing popularity of owning and riding motorcycles came the inevitable popularity of racing them, and by 1915 motorcycle racing tracks known as motodromes began popping up across the United States and Europe (Schonauer, 2011).

In 1949, a group known as the International Motorcycle Federation, or FIM, developed the Road Racing World Championship Grand Prix. The Grand Prix was a series of motorcycle races organized at race tracks throughout Europe. Motorcycle manufacturers sponsored riders to compete with their bikes, and at the end of the tour a rider and manufacturer were crowned world champions based on race outcomes.

Over sixty years later, essentially the same competition attracts millions of spectators around the world. Now known as MotoGP, it combines dozens of the world's best motorcycle riders with the world's premier motorcycle manufacturers[1]. Hosting and broadcasting 18 races on 5 continents, MotoGP is among the most popular events for people interested in motorcycles, and consequently, is one of the best available advertising outlets for motorcycle manufacturers.

Similar to many sports, MotoGP enthusiasts frequently debate the skill of athletes competing on the tour. Specifically, they debate the skill of given riders in comparison to their competition, both past and present. The rewards scheme of MotoGP is a points based one. Riders attempt to finish a race as quickly as possible, and are awarded points based on their place in the finishing order, with the earliest finishers receiving the most points. At the end of the season, these points are tallied, and the rider with the most points is crowned world champion.

Presently, these points are the most common measurement employed by fans and analysts for the comparison of riders. However, these figures are a flawed means of measuring rider talent for a bevy of reasons. In this paper, track and results data from MotoGP races from 2006-2013 are analyzed to generate a raw talent estimate for every rider. These talent estimates incorporate a wide variety of information not considered by the points system, and thus have the potential to more accurately compare and rank riders.

II. Ranking and Sports Literature

Economists have used quantitative analysis to examine competitive environments for some time now. Buhlmann and Huber (1963) discuss various methods of comparing and ranking results of three party tournaments. A hypothetical Chess tournament is used as an example. They explain the need for different approaches in ranking for different tournaments, dependent upon

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[1]The number of manufacturers sponsoring riders varies across seasons. It has been as few as 3 and as high as 8.

these different tournaments' underlying probability structures. Buhlmann and Huber (1963) consider a question inherent in all issues surrounding tournament rankings; given a specific class of competitors and a corresponding loss function, how does one find a ranking procedure which is uniformly best amongst invariant procedures (Buhlmann and Huber, 1963).

Buhlmann and Huber (1963) address two main issues, a reduced ranking problem and a general ranking problem. In their reduced ranking problem analysis, the pair explains that an ideal ranking procedure is one in which the predicted rankings are most likely to correspond to the rankings of the actual outcome of the event. In their general ranking problem consideration, Buhlmann and Huber (1963) explain the limitations of their reduced ranking considerations. They show that without the presence of a very limited class of competitors, or a highly unrealistic loss function, creating an accurate ranking procedure for a tournament is highly problematic. Still, they show the importance of developing a ranking procedure that at its base adheres to the simple tenants of their model. The lion's share of issues in developing an accurate ranking procedure come when considering large data sets.

Others consider the specific metrics used to compare and rank competitors. Utt and Fort (2002) examine the practice of using Gini coefficients of wins amongst sports teams in specific leagues as a means of judging competitive balance in those leagues. Gini coefficients are used to measure the inequality of outcomes in play amongst a league's teams. Utt and Fort (2002) examine the uses of these coefficients for the purposes of measuring competitive balance amongst Major League Baseball and National Football League teams for the 1985. They arrive at two separate conclusions for why using this metric is problematic in judging competitive balance. First, the Gini coefficient fails to account for the fact that contests within a league, while zero sum, allow participants to win only the matches they participate in, and not the entirety of duels. Thus, one participant can only control its portion of match victories, and not the entire league's (Utt and Fort, 2002). Additionally, the Gini coefficient representing a team's control of victories does not take into consideration the fact that participants in a league do not necessarily play one another, nor does it consider that teams do not necessarily play the same amount of contests. Utt and Fort (2002) account for these two issues and generate adjusted Gini coefficients to compensate for them. Comparing their adjusted Gini coefficients to the winning percentage Gini coefficients used by others, they find that the winning percentage Gini coefficients seriously miscalculate the differences in competitive balance within a league. Because of this, they recommend avoiding the pitfalls of using Gini coefficients altogether, and instead recommend using the standard deviations of team's winning percentages as a basis for competitive balance comparisons in the future.

Furthermore, economists have used historical data to generate rankings for agents based on historical performance. Joe (1990) uses a linear paired comparison model to generate rankings for the top 64 Chess players in the world from 1800-1987. After developing a criteria for determining the peak years of a player's career, Joe (1990) uses this linear model to generate rankings for each player. The model takes into account information compiled from various Chess publications on whether a given player played as white or black, whether they won, lost or drew the match, and whether or not they played participated in the match during their peak performance period. The results of this regression are rankings of the best Chess players of the 187 year period. These results bear some resemblance to simple descending win-loss ratio rankings. However this model considers a great deal more information than more simplistic models. More complete data would heighten the accuracy of this model. Specifically, data on lengths of matches in terms of both number of moves, as well as actual time passed, would allow for a much more comprehensive estimation of rankings (Joe, 1990).

In a similar vein, Torgler, Schmidt and Frey (2006) develop a regression analysis to estimate the effect of compensation differences on player performance. Specifically, Torgler et al (2006) set out to discover the impact of not only the differences in players' absolute compensation, but the differences in players' compensation relative to their teammates as well. The group notes that researchers are torn in their beliefs regarding promotion tournaments and the incentives they create in participants. Many argue that "frustration of those with a low position leads to resignation and poorer performance. Others hypothesize that a larger positional difference induces individuals to try to achieve a higher position, and thus raises performance (Torgler et al, 2006)." Torgler et al (2006) suggest that a combination of both these factors influences participant effort in a promotion tournament. To evaluate this hypothesis, the group collects performance and compensation data from the world class German soccer league *Bundesliga*. Specifically, they compile information on 1040 players over the course of 8 seasons, including player salaries, player salaries relative to their teammates, goals, assists, position and which specific team the athlete played with. Torgler et al (2006) then develop a series of ordinary least squares regressions estimating player performance, with control variables representing individuals' performance, and dummy variables specifying individuals' teams. They find that not only does a player's absolute compensation have a significant effect on their performance, but that their compensation relative to their teammates does as well, with results suggesting positive relationships with performance for both measures.

Quantitative analysis has also been used to examine the affect tournament compensation structure has on participants. Lynch and Zax (2000) analyze the effect of tournament compensation structure on track and field events in the United States. Using data from the USA Track and Field Road Running Information Center for 1994, and the 1993, 1994, and 1995 editions of the *Road Race Management Guide to Prize Money Races and Elite Athletes*, Lynch and Zax (2000) examine the behavior of runners with respect to tournament theory. Using a truncated regression with finishing time in seconds as the dependent variable, racer age and differences in prizes between races as controls, and dummy variables representing runners' gender, Lynch and Zax (2000) find that runners perform better in races when the loss in prizes they would suffer from posting a time slower than the one expected of them is greater. However, when runner skill level is accounted for using through the use of fixed effects or world rankings, this difference in performance becomes almost non-existent. Moreover, they find that races with larger prizes do not report better times because all racers are encouraged to run faster, but simply because they attract better runners.

Von Allmen (2001) performs a less sophisticated analysis of compensation structure's effect on athletic outcomes. Using data from the *NASCAR Review and Press Guide* (1999, 2000) and the *NASCAR Media Guide* (2000), Von Allmen (2001) assesses the efficiency of NASCAR's compensation structure using a handful of basic functions to determine the marginal revenue of effort exertion on the part of drivers. They find compensation for single races within the season to be a generally linear function, with cash winnings and points awarded for drivers decreasing as their placement in the finishing order rises. Conversely, they find that end of season rewards produce a highly non-linear compensation structure, whereby the points leader for the entire season wins the championship, as well as the largest share of the $5 million pot that is unequally divided amongst the top 25 drivers of the season. Von Allmen (2001) finds that this distortion in the linearity of compensation structure results in drivers behaving in inexplicable and ultimately irrational ways. Additionally, he finds both compensation structures to be inefficient in eliciting maximum effort from drivers, with the end of season rewards structure causing more inefficiency than single races' reward structures. This inefficient behavior can be attributed to the "complex utility function of teams" (Von Allmen, 2001) that includes the desire to maintain consistent sponsorships and results, as well as the desire to cooperate with teammates.

III. Related Literature

Economists have previously explored the development of motor sport rankings through the use of econometric analysis. Eichenberger and Stadelmann (2009) explore the rankings structure of the international automobile racing tour Formula 1. A detailed description of Formula 1's competitive and rewards structures is presented in Appendix 1A. To develop rankings that isolate driver talent from all outside factors, Eichenberger and Stadelmann (2009) collect results data on 768 Formula 1 races from 1950-2006, and develop an ordinary least squares regression to estimate the impact driver efforts have on a race outcome. Within those races, 719 different drivers participated in races, but for the purposes of managing computational difficulty, only the 302 drivers who scored at least one point and participated in 40 races throughout their career were examined.

Eichenberger and Stadelmann (2009) include data on the length of these races in kilometers, circumference of racetracks in meters, and the number of laps in races to use as controls in their model. They also develop a classification matrix to grade weather on the day of these races to control for track conditions. Weather is graded on a scale from -2 to 2, where -2 represents the least ideal of racing conditions and 2 represents the most ideal conditions. Additionally, they include data on drivers' ages at the beginning and end of their careers to account for driver experience. Data expressing the number of times a driver has switched teams, the number races a driver participated in, as well as the number of first place or podium finishes they recorded is also included.

Data on the finishing order of drivers for each race is compiled for use at the model's dependent variable. "If a driver finished the race, his classification corresponds to his achieved race classification (Eichenberger and Stadelman, 2009)" If a driver failed to finish a race, the cause of his failure, human error or machine failure, is examined. For human error caused failures, a driver's classification is set to the classification of the last driver finishing the races, plus the number of drivers not finishing the race divided by two. Thus, all drivers failing to finish a race because of human error achieve the same classification in that race, and this classification will never be as good as if they were to have finished the race. Drivers who fail to finish a race due to mechanical failure are controlled for with a dummy variable.

Eichenberger and Stadellman (2009) then generate dummy variables representing individual drivers, and the model year cars they operated. Driver dummies remain constant throughout the dataset, as it is assumed driver talent remains at the same level throughout their careers. Car dummies specify each manufacturer's car for each season to account for technological progress in the cars' development, as improvements are made to the model after every season.

An ordinary least squares regression is then performed. Eichenberger and Stadelmann (2009) use driver classification as their dependent variable, and regress this by the driver dummy variable, car-year dummy variable, and the control variables mentioned earlier. The results include coefficients for each driver dummy variable, which represent the corresponding driver's placement in a hypothetical race. By controlling for the effects of different cars through dummies, as well as the effects of different tracks and conditions, the resulting coefficient for driver dummy variables represents where each driver would finish in a race with a hypothetical perfectly level playing field. In other words, this coefficient represents the raw talent of each driver, with a lower coefficient signifying greater talent. No constant is employed in this regression, as it would only serve to uniformly increase the classification of each driver in the hypothetical race.

Eichenberger and Stadelmann (2009) find that drivers from earlier periods of Formula 1 rank higher than their modern counterparts. This could be due to any number of factors, but they suggest this could be the result of fiercer competition amongst the highest tier of drivers in earlier periods. Manufacturers also began to increase their focus on car engineering and pit crew improvements later on in the sport's history, whereas finding the best driver was their chief focus in earlier eras. Eichenberger and Stadelmann (2009) test their results for robustness by comparing the results from their first regression to the results of a regression including variables controlling for the classification of a driver's teammate and experience of the driver. They find that a teammate's classification has little bearing on a given driver's classification. Experience returned a positive coefficient result when included, suggesting that drivers with more experience fare better than their lesser experienced counterparts, but these results were not significant.

IV. Methodology

The data for this paper is extracted from one source, MotoGP.com, the official website of MotoGP. The website contains databases with the finishing order of every race from 1949-2014.

It also contains statistics for nearly every course raced on within this time period, as well as career statistics and biographical information for many riders. However, the data is limited in that MotoGP only began taking official climate and track condition measurements at the start of the 2006 season. For this reason, I focus on data from the 2006-2013 seasons[1]. The database includes a wide offering of data for races and riders within these seasons. Eichenberger and Stadelmann (2009) developed a classification matrix to grade weather from ideal to hazardous, in part because accurate climate information was not available for all periods of their data set. MotoGP lists specified climate information in their database, including air temperature, track temperature, and humidity at the racetrack on the day of the race for all races from 2006 on. They also specify whether the track was wet or dry at the beginning of the race. This data is of importance due to motorcycle racing's particular sensitivity to weather conditions. Successfully navigating a motorcycle race course is a difficult proposition, and this difficulty increases with the loss of tire traction experienced on a wet surface, or a track that is too cold[2]

I use data regarding unique track features as controls, Table A in Appendix 1B describes these variables. These controls include the number of both left and right turns in a track as well as the length of the longest straight section of a track in meters. I also include the year the track

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[1]The MotoGP season is structured so that the final race falls at the end of November, data for the 2014 season was not available in time for this analysis

[2]Tire traction is key to motorcycle racing. It allows a rider to control the movement of the bike via the tires. Wet surfaces reduce traction. Cold surfaces impede tire heating via friction, and hotter tires generate more traction.

was constructed or modified to account for rider familiarity with the course, as well as a dummy variable representing the side of pole position of the track.[1] Additionally, I include the number of years a rider has participated in MotoGP as a control for rider experience. Eichenberger and Stadelmann (2009) create dummy variables to represent each individual rider and model-year car. I emulate this approach and create dummy variables for each rider and model-year motorcycles.

I use an ordered logistic regression, and regress finishing order results on both rider and model-year motorcycles, in addition to the aforementioned control variables. For the purposes of easing computational difficulty, I consider only riders who have competed in more than 20 races from 2006 on. Eichenberger and Stadelmann (2009) generate counterfactual rankings to represent human error caused failures to finish, and dummy variables to represent mechanical failure caused failures to finish. No specification between human error caused failures to finish and technical error caused failure to finish is made in the MotoGP results database. However, races generally contain 18 to 24 participants, so I classify all riders that fail to complete the race as arriving in 25th place, which ensures that all riders are classified and that it is never better for a rider to drop out of a race as opposed to finishing it.

[1] A rider occupies the pole position when they are in the front row of racers at the beginning of the race, and they are positioned in the starting grid so as to have the best advantage headed into the first turn. Riders compete in qualifying laps to set their best lap times, and starting order is determined by these lap times. The fastest qualifying rider gets pole position on race day, and it is either the on left or right side of the track

Table 1

Variable	Coefficient	Standard Error	P-Value
Loriscapirossi	.665	.414	.108
Danipedrosa	-3.553	.225	0
Nickyhayden	-.997	.259	0
Tonielias	-.407	.233	.081
Marcomelandri	-1.003	.234	0
Caseystoner	-3.753	.231	0
Shinyanakano	-.101	.267	.704
Colinedwards	-.150	.255	.555
Kennyrobertsjr	.385	.446	.388
Johnhopkins	-.620	.302	.04
Makototomada	-.260	.288	.368
Carloscheca	1.568	.458	.001
Valentinorossi	-2.089	.360	0
Alexhofmann	.177	.323	.583
Jamesellison	.976	.312	.002
Randydepuniet	.101	.201	.616
Setegibernau	.525	.498	.291
Ivansilva	1.129	.386	.003
Alexbarros	1.007	.623	.106
Sylvainguintoli	.593	.311	.057
Olivierjacques	1.998	.892	.025
Nobuatsuaoki	1.074	1.049	.306
Jorgelorenzo	-4.583	.231	0
Andreadovizioso	-2.586	.202	0
Jamestoseland	-1.283	.310	0
Benspies	-1.856	.272	0
Aleixespargaro	-.627	.239	.009
Hiroshiaoyama	-.589	.254	.02
Marcosimoncelli	-2.132	.329	0
Hectorbarbera	-0.720	.226	.001
Alvarobautista	-1.894	.244	0
Calcrutcrutchlow	-2.114	.285	0
Karelabraham	-.264	.300	.38
Stefanbradl	-2.758	.319	0
Yonnyhernandez	.004	.313	.989
Michelepirro	-.778	.339	.022
Danilopetrucci	-.070	.300	.816
Marcmarquez	-5.573	.448	0
Andreaiannone	-.840	.464	.07
Michaellaverty	.087	.392	.823

Bradleysmith	-2.092	.412	0

Prob>Chi2	0.000	Log Likelihood	-6906.8335 (6th Iteration)
Psuedo R^2	0.090		

Orderer Logistic Regression, 143 Panels with 2639 Observations each

Each rider's dummy variable coefficient, when significant, indicates a change in the logarithmic odds of being in the higher levels of finishing order. For example, the coefficient of the dummy variable representing Valentino Rossi is -2.089. This indicates that when the variable is equal to one, there is -2.089 increase in the logarithmic odds of finishing late in a race. With Prob>Chi2 equal to 0, these coefficients can be accepted.

If a negative coefficient for rider dummies signifies a decrease in the chances of a given rider finishing later in a race, then taking the significant regressors and ordering them from lowest to highest produces what can be interpreted as a talent ranking, with the lowest scores corresponding to the most talented riders. Table B in Appendix 1B displays the top ten riders according to this regression. The model controls for outside influences on rider performance, so the riders whose dummies' coefficients represent the greatest decrease in the likelihood of finishing later in a race are the riders who can be expected to finish earliest in a race where outside influences are controlled for.

Comparing the rankings of riders based on their dummies' coefficients in this model to other ways of ranking riders yields interesting results. Comparing the regression results to the 2013 season points standings listen in Table D in Appendix IB, one notices that many of the same names occupy the tops of both lists. However, a few aspects of the regression results indicate that it takes into account factors in ranking rider skill that the points scale has overlooked. The top ten list of riders ranked by the regression contains two names that seem out of place when comparing them to the total points list rankings, Casey Stoner and Marco Simoncelli.

Casey Stoner is a two-time MotoGP world champion (2007, 2011) who was widely regarded by analysts and contemporaries to be one of the most talented motorcycle riders of all time. However his performance was unreliable at times, and in 2012 he announced that he had been suffering from depression throughout his time in MotoGP, and that he would be retiring from the sport to deal with this. The model ranks him as the 3rd best rider of the field considered, while the cumulative points ranking has him falling significantly further down over the same period. Points inherently award consistency in performance, a rider who finishes in 3rd place for five straight races will receive nearly double the points that a rider who finishes in 1st in one of those races, and the rest in 11th. It is likely that Casey Stoner was more than capable of beating many of the competitors that topped the points list after he departed, but because of his inconsistent performance and premature retirement, his talent is negated when examining the points rankings.

Much like Stoner, Marco Simoncelli was a star among his peers at every level of racing in which he competed, and MotoGP was no exception when he arrived in the 2010 season. After a shaky start to the season, Simoncelli consistently improved, finishing out the season in 8th place in the points standings. He continued this success from the start of the 2011 season, overcoming disciplinary penalties for dangerous riding to still finish near the top in multiple races. Tragically, Simoncelli was killed in accident during an October 2011 race. Thus his 1.5 season long career had no hope of being considered for the top of career points list, even for a dataset as relatively small as the 2006-13 on examined, and consequently his name appears in no substantial rankings list for MotoGP riders. However, Simoncelli falls into 7th place on the list of riders ranked by regression coefficients. This suggests that the model effectively controls for the length of a rider's career when determining his ranking in relation to other riders that might have competed for greater lengths of time.

For these reasons, it can be argued that using econometric analysis to develop a ranking model for MotoGP rider talent is a more effective method of determining rider skill than observing their cumulative points earned or championships won throughout their career. While useful for quick organization, these more simple ranking methods fail to account for a variety of important factors to consider when judging the quality of a MotoGP rider. These methods are presently the only popular methods of ranking riders, and as a result a great deal of interesting information about great competitors is lost on parties that are new to the sport, or steadfast in their ways of considering talent. There are also economic implications to consider when evaluating the effectiveness of the regression's ranking results in comparison to the more simple models. For example, Table D in Appendix 1B displays the top ten salaries paid to MotoGP riders for the 2014 season, and the riders that received them. The payment structure from manufacturers to the riders they have chosen to sponsor seems to be based more so on the simplistic models of ranking, like total career points or championships, than on the talent of riders themselves. Certainly, factors not controlled for in the regression model, like rider popularity or prior relationship with a manufacturer, should be considered before judging these manufacturers' selection of riders too harshly. However, the results of the regression suggest that some companies vastly overcompensated their selected riders for their talent, while leaving far more talented riders for other manufacturers to sponsor. A great deal of this could likely be explained through an analysis of MotoGP's compensation structure in a manner similar to the methods employed to judge NASCAR's compensation structure by Von Allemen (2001).

V. Conclusion

The results suggest that there is promise to using econometric analysis as a way of developing a more effective method of ranking MotoGP riders' abilities separate from their bikes, teams, and engineers. The shortcomings of currently popular models in accurately expressing rider talent are numerous. These problems include issues as obvious as failing to account for the length of riders' careers in comparing their achievements, and not considering the fact that riders must compete with one another on different machines. However these models also have more deep-seeded problems in ranking riders, such as an inability to adequately represent the achievements of athletes that have died in an incredibly dangerous sport. Using a regression in favor of these models can adequately address these issues.

More research is needed to explore other variables that might have a significant effect on riders' rankings relative to their competition. Additionally, data from a time period larger than 8 seasons would examine what makes a rider better or worse than his competition more effectively than the present model, as many riders have careers that span longer than a decade.

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Appendix 1A. Formula 1 & MotoGP Racing and Rewards Structure.

Formula 1 is the world's preeminent automobile racing tour. It consists of numerous teams sponsored and supplied by manufacturers, competing against one another in a series of races. Each racer has at least one "teammate" sponsored by the same manufacturer. Racers compete against one another to finish first in races to win the most points. Points are awarded to drivers according to their placement in the finishing order. Points are distributed as follows: 1st place- 25 points, 2nd place-18 points, 3rd place-15 points, 4th place-12 points, 5th place-10 points, 6th place-8 points, 7th place-6 points, 8th place-4 points, 9th place-2 points, 10th place-1 point. Remaining finishers are awarded no points. At the end of the season, whichever rider has the most points is crowned world champion. Teammates compete against one another in races, but the points from their efforts are combined to create scores for their sponsoring manufacturers as well. Whichever manufacturer has the most cumulative points amongst its drivers is awarded the Constructor's Championship.

MotoGP is essentially structured the exact same way as Formula 1, including driver and manufacturer championships. However, points are awarded to riders for their classification in the finishing order differently. Points are distributed to MotoGP finishers as follows: 1st place- 25 points, 2nd place-20 points, 3rd place-16 points, 4th place-13 points, 5th place-11 points, 6th place-10 points, 7th place-9 points, 8th place-8 points, 9th place-7 points, 10th place-6 points, 11th place-5 points, 12th place-4points, 13th place-3 points, 14th place-2 points, 15th place-1 point. All remaining finishers receive no points.

Appendix 1B. Assorted Tables

Table A

Variable	N	Min	Max	Mean
Rider Experience	79	0	16	9
Air Temperature	142	51	102	75
Track Temperature	142	50	143	92
Left Corners	22	4	11	7
Right Corners	22	4	12	8
Longest Straight	22	450	1202	843
Year Constructed/Modified	22	2012	1974	1997

Table B

Rider	Coefficient	P-Value
Mark Marquez	-5.573	0
Jorge Lorenzo	-4.583	0
Casey Stoner	-3.753	0
Dani Pedrosa	-3.553	0
Stefan Bradl	-2.758	0
Andrea Dovizioso	-2.586	0
Marco Simoncelli	-2.132	0
Cal Crutchlow	-2.114	0
Bradley Smith	-2.092	0
Valentino Rossi	-2.089	0

Table C

1	**Marc MARQUEZ**	**334**
2	**Jorge LORENZO**	**330**
3	**Dani PEDROSA**	**300**
4	**Valentino ROSSI**	**237**
5	**Cal CRUTCHLOW**	**188**
6	**Alvaro BAUTISTA**	**171**
7	**Stefan BRADL**	**156**
8	**Andrea DOVIZIOSO**	**140**
9	**Nicky HAYDEN**	**126**
10	**Bradley SMITH**	**116**

Table D

1	**Valentino Rossi**	**$12m**
2	**Jorge Lorenzo**	**$7.2m**
3	**Marc Marquez**	**$4m**
4	**Dani Pedrosa**	**$3.9m**
5	**Cal Crutchlow**	**$1.9m**
6	**Stefan Bradl**	**$1.2m**
7	**Alvaro Bautista**	**$900,000**
8	**Nicky Hayden**	**$1.3m**
9	**Andrea Dovizioso**	**$1.0m**
10	**Scot Redding**	**$650,000**