

Who Is The Best Formula 1 Driver? An Economic Approach to Evaluating Talent

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Abstract: Who is the best formula 1 driver? Until today it was impossible to answer this question because the observable performance of a driver depends both on his talent and the quality of his cars. In this paper, we for the first time separate driver talent from car quality by econometrically analyzing data covering 57 years of Formula 1 racing. Our estimates also control for the number of drivers finishing, technical breakdowns and many other variables that influence race results. While Michael Schumacher is often believed to be the best driver, he is overtaken by Juan Manuel Fangio and Jim Clark.

I. INTRODUCTION

Who is currently the best Formula 1 driver? Who was the best Formula 1 driver in history? And what about the Australian drivers? Many people are more interested in such questions than in the very important research puzzles commonly dealt with in economic journals. Fortunately, these questions can be answered thanks to the tools used by economists.

A Formula 1 driver is fast, if he is talented and has a good car. Moreover, his racing success depends on a large number of additional factors. Individual success is determined to a large extent by factors such as the competitors' talents and the quality of their cars, the number of competitors in a race, weather conditions during the race, and pure racing luck. Current rankings of Formula 1 racers provided by racing magazines and on the internet do not separate the qualities of the drivers and their cars, nor do they recognize the influence of other determinants of race outcomes. Usually, such rankings represent the simple sum of points, races won, podium positions achieved or similar measures. The resulting rankings are often not even corrected for the number of races a driver participated in, even though it is evident that competing in more races leads, *ceteris paribus*, to more points, podium positions and wins.

Econometrics provides tools to improve current rankings by calculating an estimate for a Formula 1 driver's talent independently of his car and other factors. A talent estimate can be obtained by multiple regressions. Formula 1 is a competition among teams. Generally speaking, a team consists of two drivers who use identical cars. As the drivers and their team

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partners change over time, the contribution of a driver and a particular car can be technically separated. In addition, other factors influencing race outcomes can serve as controls.

In this paper we analyze a dataset from the start of Formula 1 racing in 1950 up to 2006 and calculate talent estimates for every driver. Thereby, we establish a historical world championship ranking which is based on the true talent of Formula 1 drivers. According to our results Michael Schumacher has been the fastest driver of the last three decades but he is not better than Formula 1 superstars of times gone by, such as Juan Manuel Fangio and Jim Clark. Apart from Schumacher, more recent drivers such as Fernando Alonso and Kimi Räikkönen enter the all time TOP-10 champion's list.

Today, the economic analysis of sports is a broad research area. The number of contributions concerning specific topics linked to sports is growing quickly. A number of specialized journals¹ and the recent Handbook of the Economics of Sport by Andreff and Szymanski (2007) confirm this trend. There also exists an increasing number of books in the field (see for example Ford, 2007) as well as review articles summarizing recent studies (see Szymanski, 2003). This literature usually focuses on typical problems of sports which are analyzed from an economic perspective. However, some authors take a different route by using sports and sports competitions to analyze economic problems: Rosen and Sanderson (2001) focus on issues in labor economics by analyzing sports competitions and Torgler, Schmid and Frey (2006) use data from soccer players to analyze the impact of changes in monetary compensation on motivation. Similarly, Kahn (2000) argues that data from sports competition may serve as an important source to answer urgent economic questions linked to individual incentives, monopoly power and discrimination.

In sport economics, existing rankings are usually used as a measure for talent. In contrast, economic analyses aiming to evaluate talent itself are rare. This is surprising as in many sports the quality of an athlete depends largely on the quality of the material he or she uses and on the quality of his or her team. Skiing, horse riding, soccer, football and, today even swimming serve as just a few examples how the quality of the material used and team may heavily influence an athlete's results. We have performed an econometric analysis of talent of Formula 1 drivers. Our approach is closely related to Lynch and Zax (2000) who analyze the effects of changes of the incentive system in racing via multiple regressions with fixed effects.

The remainder of this paper is structured as follows: Section 2 presents the data analyzed. Section 3 focuses on the model and the method to evaluate a Formula 1 driver's talent. Section 4 presents the most important results which are tested for their robustness in section 5. In section 6 we discuss potential drawbacks of our estimation method while section 7 summarizes the results and suggests future research questions.

II. DATA

The internet database "FORIX" by the magazine "Autosportatlas" represents the main source of information for our estimations. Additional information and variables were coded using the

¹ Apart from the Journal of Sports Economics there exists the International Journal of Sport Finance, the Journal of Sport Management, the International Journal of Sport Management, and the International Journal of Sport Management and Marketing.

official Formula 1 website formula1.com. The dataset constructed includes 768 races from the start of Formula 1 in 1950 up to 2006.² During these 57 years, 801 drivers registered for races and 719 of them actually started. 302 racers achieved at least one point during their career while 97 have won at least once and 55 drivers have won at least three times.

At the beginning of Formula 1 racing, many rather inexperienced drivers participated in Formula 1 racing without clear career perspectives. They often remained in Formula 1 for a short time. Thus, their results depended heavily on fortune. Consequently, they may bias our estimates. Moreover, using 719 drivers would lead to a data matrix which could only be handled with computational difficulty. Thus, we only analyze the 302 drivers who achieved at least one point during their career.

A driver's pure luck becomes less important statistically if the number of his race participation increases.³ When presenting the results we consequently focus on drivers who participated in at least 40 races. 40 races approximately represent three racing seasons when the whole dataset is analyzed. This also represents a sufficiently large number of car changes and changes of team partners in order to systematically compare the drivers. The general ranking reacts robustly to changes in these statistical choices.

Table A1 of the Appendix provides an overview of the data for the 302 racers and the 768 races. Most of the descriptive statistics are evident such as length of the race (GRANDPRIXDIST), circumference of the track (CIRCUMFERENCE), rounds in grand prix (ROUNDSP), weather conditions (WEATHER), age of the drivers at their career start (AGEDRIVERSTART) and end (AGEDRIVEREND), number of races per driver (DRIVERSINRACE), successful participations of drivers in wins (DRIVERSWINS), podium positions (DRIVERSPODIUMS) of drivers, and car changes (DRIVERSCARS). Here, we only focus on some constructed and interesting measures.

The WEATHER variable is an integer between -2 (bad weather) and +2 (good weather) where 0 represents the weather condition denoted "partly cloudy, mild, partially wet". Thus the coding focuses rather on bad weather conditions. Especially these conditions are more difficult for drivers than good conditions.

The distribution of first and podium positions differs largely with respect to race participations. Drivers winning races are clearly outliers. The median of races per driver is 31 while the median for first position is zero. A quick glance at races in points (absolutely and relatively) in *Table 1* confirms this picture. The median of podium positions equals one. Winning and podium positions also have a comparatively high standard deviation compared to the mean. This is a clear indication that differences in talent mirror some form of "superstar effects" (see Rosen 1981). Only some drivers really manage to win and to obtain high monetary compensations.

² Unfortunately, in this paper we cannot provide more recent results. In the last three years there were a large number of young racers entering Formula 1. In order to evaluate their performance we need at least the results of the whole racing season 2009 in order to get statistically stable results.

³ Consider the American Lee Wallrad for example. He won 50 % of the Formula 1 races he participated in. But he only participated in two races and those two were held in Indianapolis under special conditions.

III. EVALUATING TALENT

The racing position of every Formula 1 driver is a function of a number of important impact factors such as their individual talent, the quality of their cars as well as other race-specific variables, such as weather conditions, characteristics of the track and home advantage, among others.

The dependent variable of this analysis is denoted as \mathcal{Y}_i and represents the classification of a driver i in race t . This variable depends on the number of participants in a race which can be easily included as a control variable. Points, racing times, training times or fastest rounds represent other possible choices for a dependent variable but these measures suffer serious drawbacks in comparison to the variable race classification. The main aim of a driver and a team is to achieve a good classification and to obtain many points during a season. However, *points* are not a good choice as a dependent variable. Firstly, points are only attributed to the first six or eight classifications and thus differences in the performance of drivers without points could not be distinguished although they make an important difference for drivers and their teams. Secondly, the sum of points achieved also depends more on luck than the classification achieved. Thirdly, the number of points per classification was adjusted over time due to changes in racing rules. This makes comparisons using this measure complicated and unreliable. *Racing time* is neither an appropriate measure for success because it depends heavily on racing strategies. Especially in the final phase of a race advanced drivers may slow down and drive to “hold their position”. Additionally, technical progress and changes in safety on routes have led to significant changes in racing times over the last decades. Finally, *training times* are also not a reliable measure of performance. While they contain information on the overall speed of a driver they also depend largely on a team’s strategy. In recent years it was forbidden to refuel the vehicle after training and before the race. Thus, cars with significant differences in fuel and therefore in weight participated in the qualification training, biasing training times.

In our estimates every driver needs to have a unique classification for comparisons with other drivers. On the one hand, if a driver has finished a race his classification corresponds to his achieved race classification. If, on the other hand, he has not finished the race, we have to calculate a counterfactual classification. In our dataset we can distinguish between “human dropouts” and “technical dropouts”. “Human dropouts” are due to accidents, collisions and disqualification, while “technical dropouts” are due to engine failures, problems with tires and so forth. As technical dropouts are not directly linked to a driver’s talent, we control for such dropouts with a dummy variable. For human dropouts we calculate a hypothetical classification. There is no information available on the ranking of a driver during the time of dropout. Thus, we set counterfactual rankings for human dropouts which equals the classification of the last driver arriving plus the number of total dropouts divided by two. If, for example, 22 drivers out of 10 (12) arrive and 12 (10) drop out then the classification of dropped out drivers equals 16 (17). Consequently, a dropout is always worse than achieving a classification. Moreover, a human dropout’s contribution to the driver’s ranking worsens if more drivers finish the race.⁴ Naturally, we test whether our results react robustly to variations in the treatment of human dropouts.

⁴ It could be argued that certain drivers prefer to drop out instead of arriving last. Though, looking at historical data it seem that even top drivers finish a race if they lag behind due to technical problems.

Our model contains a separate dummy variable α_i for each driver. Additional controls for the car used as well as other control variables which influence the classification of a driver are included. These additional controls are not directly correlated with a driver's talent and we summarize them in a sub-design matrix, X . Control variables for the car used in a race draw on all available technical information of the type of the racing car. As each team invests heavily in order to improve the car, the absolute quality of each car improves with each racing season. Even if a car is not successfully developed further, it changes its relative quality as the other teams are improving their cars. Therefore, entering only dummies for the type of car or the name of the team is not sufficient. Rather, it is necessary to identify unique car types for each year. Thus, we construct for every car in combination with the year, a car-year-specific dummy which is employed as a separate control variable $\gamma_{s,i}$. All car-year-specific dummies are attached to the respective drivers in our matrix design. An example for such a dummy variable is the Alfa Romeo 159 of the year 1951 which is denoted in our matrix as `AlfaRomeo159_1951` or the Lotus 107 of the year 1993 which is denoted as `Lotus107_1993`. By construction of these car-year-specific dummies, we effectively control for car and year-specific effects. Therefore, we prevent drivers who can use an improved type of car earlier than their team partners from obtaining an unfair advantage.⁵ Using car dummies and year dummies separately by including year-specific effects would not serve this aim. Year-specific effects are not car-specific and vice versa. Finally, this construction allows us to control for dynamic and strategic effects. Our preferred specification includes driver-specific effects, the previously discussed car-year effects, controls for the number of competitors finishing the race, technical dropouts and weather conditions as well as the length of the grand prix.⁶

In order to include all drivers in the analyses, we do not use a constant. The estimated regression estimated is given by:

$$y_{it} = \alpha_i + \gamma_{s,i} + X\beta + u_{it} \quad (1)$$

where α_i is a dummy variable capturing quality of driver i and $\gamma_{s,i}$ represent car-year-specific effects. X is the design matrix of the other control variables and β its corresponding coefficient vector. u_{it} stands for the error term. While driver and car-year-specific effects enter all estimates, we analyze the sensitivity and robustness of our results by changing the control variables in the design matrix. The variable `DRIVERFINISHING` fluctuates largely over the years 1950 to 2006. This indicates that dropouts had a different effect in different time periods. Consequently, we need to identify periods which are comparable in order to achieve a consistent ranking over time. The identified dropout periods are then interacted with the variable controlling for dropouts. The different dropout periods can be directly identified using the dataset. Relative dropouts per race for different time periods are averaged. The different dropout periods are then compared using statistical tests. If the differences in the two groups (two periods)

⁵ Our design matrix contains in its columns 1291 dummy variables of all drivers and all cars plus additional control variables. Due to singularities, i.e. linear combinations of drivers' columns, we had to eliminate four drivers who either did not have a team partner or whose team partner did not use the same car model. None of these drivers participated in more than 40 races.

⁶ The variable `DRIVERFINISHING` is also used as an interaction term when identifying special drop out periods.

are sufficiently large, i.e. at the 1-%-level, we have identified a unique dropout period. If differences between periods are not statistically significant, we build a new group and repeat the identification algorithm. Finally, only significant dropout periods remain.⁷

A feasible alternative to our linear regression model would consist of estimating an ordered probit model for the variable classification. However, the large number of independent variables, i.e. the large number of driver, car-year controls, etc. induces problems with convergence. As the number of possible classifications is sufficiently high a linear fit is comparable to a probit model. Still, Stadelmann and Eichenberger (2008) provide a probit model and the results are comparable to the ranking presented here. The results are also robust.

IV. RESULTS AND RANKING

From the linear regression model we obtain a unique driver coefficient α_i of the dummy variable for every racer. This coefficient serves as an indicator for a driver's talent. The lower the value of the coefficient the better the Formula 1 driver. *Table 1* shows the results and column (1) gives our preferred specifications for 124 drivers who have participated in at least 40 races. Columns (6) and (7) serve as comparisons. In column (6) we simply summed the number of races in points while in column (7) we summed the number of races with wins. We distinguish between the relative number of races in points and wins and the absolute number of races in points and wins. The relative measures represent the number of races in points divided by the number of races itself and the number of wins divided by the number of races, respectively.

All drivers are ordered according to their results in column (1). The index behind each value in a cell represents the ranking of the driver within the respective column. For every coefficient of the driver dummy we indicate the standard error which is below the coefficient in parentheses. As no constant is included in the model and a classification cannot be greater than one, the standard error should not be used to test the standard hypothesis "coefficient equals zero". The standard error serves as a measure for comparisons and to estimate confidence intervals.

We do not include coefficient estimates for the control variables in *Table 1*. They all have the expected signs. In our preferred specification (1) the variable DRIVERFINISHING is significant and positive. The more drivers finishing a race, the more difficult it is to achieve a good classification. The interaction terms of the dropout periods with this variable are insignificant. A Wald-Test for their joint significance rejects the null hypothesis (p-value 0.001; F-value of Wald-Test 3.997). The control for technical dropouts TECHOUT is positive and highly significant as expected. Weather conditions have a negative and significant influence. As there are more human dropouts when the weather is bad, the average classification increases during bad weather. The length of a Grand Prix is also negative but does not have a significant influence (11-%-level). Thus, we have the following results for the control variables of specification (1)⁸:

⁷ *Table A2* in the Appendix shows the resulting dropout periods.

⁸ Standard deviations are given below coefficient values.

$$\begin{aligned}
 \text{Classification} &= (\text{Driver Effects}) + (\text{Car-Year Effects}) + \\
 &+ \frac{0.1105}{(0.04681)} (\text{DRIVERFINISHING}) \\
 &+ (\text{Interactions DRIVERFINISHING with dropout periods}) \\
 &+ \frac{8.145}{(0.07655)} (\text{TECHOUT}) - \frac{0.07986}{(0.02964)} (\text{WEATHER}) \\
 &- \frac{0.00169}{(0.00108)} (\text{GRANDPRIXDIST})
 \end{aligned}$$

The results for individual drivers, i.e. the driver-specific effects are given in *Table 1*.

Table 1: Ranking of Formula 1 drivers

Driver	(1) preferred specification	(2) Sorting and home advantage	(3) as (2) with experience	(4) Dropouts = arriving + 1	(5) as (4) with experience	(6) races in points (rel/ abs)	(7) wins (rel/ abs)
Juan Manuel Fangio <i>ARG</i> (1950 bis 1958)	5.267 ₁ (3.359)	5.565 ₁ (3.361)	5.721 ₁ (3.363)	3.247 ₁ (2.485)	3.362 ₁ (2.486)	0.843 ₁ 43 ₃₆	0.471 ₁ 24 ₈
Jim Clark <i>GBR</i> (1960 bis 1968)	6.301 ₂ (3.308)	6.599 ₂ (3.311)	6.737 ₃ (3.312)	3.740 ₂ (2.448)	3.841 ₄ (2.449)	0.548 ₁₀ 40 ₄₁	0.342 ₃ 25 ₆
Michael Schumacher <i>GER</i> (1991 bis 2006)	6.307 ₃ (3.188)	6.610 ₃ (3.191)	6.588 ₂ (3.191)	3.845 ₄ (2.359)	3.829 ₃ (2.359)	0.760 ₂ 190 ₁	0.364 ₂ 91 ₁
Jackie Stewart <i>GBR</i> (1965 bis 1973)	6.531 ₄ (3.294)	6.794 ₄ (3.296)	6.869 ₄ (3.296)	4.213 ₅ (2.437)	4.268 ₅ (2.437)	0.570 ₈ 57 ₂₀	0.270 ₄ 27 ₅
Mike Hawthorn <i>GBR</i> (1952 bis 1958)	6.807 ₅ (3.363)	7.106 ₅ (3.365)	7.207 ₆ (3.366)	4.227 ₆ (2.488)	4.302 ₆ (2.488)	0.596 ₆ 28 ₅₉	0.064 ₃₀ 3 ₄₅
Fernando Alonso <i>ESP</i> (2001 bis 2006)	6.842 ₆ (3.272)	7.148 ₆ (3.275)	7.109 ₅ (3.275)	3.802 ₃ (2.421)	3.773 ₂ (2.421)	0.625 ₄ 55 ₂₆	0.170 ₉ 15 ₁₃
Alain Prost <i>FRA</i> (1980 bis 1993)	7.150 ₇ (3.189)	7.464 ₇ (3.192)	7.484 ₇ (3.192)	4.518 ₇ (2.360)	4.533 ₇ (2.360)	0.634 ₃ 128 ₂	0.252 ₆ 51 ₂
Graham Hill <i>GBR</i> (1958 bis 1975)	7.384 ₈ (3.254)	7.672 ₈ (3.257)	7.784 ₁₀ (3.257)	5.019 ₁₂ (2.407)	5.102 ₁₂ (2.408)	0.330 ₄₉ 59 ₁₇	0.078 ₂₅ 14 ₁₄
Emerson Fittipaldi <i>BRA</i> (1970 bis 1980)	7.399 ₉ (3.265)	7.685 ₉ (3.268)	7.748 ₉ (3.268)	4.676 ₈ (2.416)	4.722 ₈ (2.416)	0.383 ₃₄ 57 ₂₀	0.094 ₁₈ 14 ₁₄
Jacky Ickx <i>BEL</i> (1967 bis 1979)	7.518 ₁₀ (3.235)	7.798 ₁₁ (3.238)	7.863 ₁₁ (3.238)	5.180 ₁₅ (2.394)	5.228 ₁₇ (2.394)	0.333 ₄₇ 40 ₄₁	0.067 ₂₈ 8 ₂₈
Kimi Räikkönen <i>FIN</i> (2001 bis 2006)	7.527 ₁₁ (3.237)	7.790 ₁₀ (3.240)	7.738 ₈ (3.240)	4.774 ₁₀ (2.395)	4.736 ₉ (2.395)	0.552 ₉ 58 ₁₉	0.086 ₂₂ 9 ₂₆
Jochen Rindt <i>AUT</i> (1964 bis 1970)	7.544 ₁₂ (3.297)	7.831 ₁₂ (3.300)	7.918 ₁₂ (3.300)	5.129 ₁₄ (2.440)	5.192 ₁₆ (2.440)	0.339 ₄₅ 21 ₆₉	0.097 ₁₇ 6 ₃₂
Dan Gurney <i>USA</i> (1959 bis 1970)	7.551 ₁₃ (3.300)	7.839 ₁₃ (3.303)	7.938 ₁₃ (3.303)	4.770 ₉ (2.442)	4.842 ₁₀ (2.442)	0.356 ₃₉ 31 ₅₂	0.046 ₃₅ 4 ₄₂
James Hunt <i>GBR</i> (1973 bis 1979)	7.714 ₁₄ (3.263)	7.982 ₁₄ (3.265)	8.034 ₁₄ (3.265)	4.982 ₁₁ (2.414)	5.021 ₁₁ (2.414)	0.376 ₃₆ 35 ₄₉	0.108 ₁₅ 10 ₂₂
Stirling Moss <i>GBR</i> (1951 bis 1961)	7.719 ₁₅ (3.316)	8.003 ₁₅ (3.318)	8.155 ₁₅ (3.320)	5.079 ₁₃ (2.453)	5.191 ₁₅ (2.454)	0.522 ₁₄ 35 ₄₉	0.239 ₇ 16 ₁₂
Nick Heidfeld <i>GER</i> (2000 bis 2006)	8.006 ₁₆ (3.223)	8.307 ₁₇ (3.226)	8.283 ₁₆ (3.226)	5.193 ₁₆ (2.385)	5.175 ₁₄ (2.385)	0.263 ₆₃ 31 ₅₂	0.000 ₇₄ 0 ₇₄
Ronnie Peterson <i>SWE</i> (1970 bis 1978)	8.029 ₁₇ (3.229)	8.304 ₁₆ (3.232)	8.367 ₁₇ (3.232)	5.455 ₂₂ (2.389)	5.501 ₂₃ (2.389)	0.341 ₄₄ 42 ₃₈	0.081 ₂₄ 10 ₂₂

WHO IS THE BEST FORMULA 1 DRIVER? AN ECONOMIC APPROACH TO EVALUATING TALENT

EliodeAngelis <i>ITA</i> (1979 bis 1986)	8.065 ₁₈ (3.236)	8.375 ₁₈ (3.239)	8.404 ₁₈ (3.239)	5.380 ₁₉ (2.395)	5.401 ₂₀ (2.395)	0.394 ₃₂ 43 ₃₆	0.018 ₅₉ 2 ₅₂
Pedro Rodriguez <i>MEX</i> (1963 bis 1971)	8.134 ₁₉ (3.327)	8.462 ₂₁ (3.330)	8.537 ₂₃ (3.331)	5.482 ₂₃ (2.462)	5.537 ₂₄ (2.462)	0.407 ₂₈ 22 ₆₇	0.037 ₄₁ 2 ₅₂
Phil Hill <i>USA</i> (1958 bis 1964)	8.171 ₂₀ (3.338)	8.454 ₂₀ (3.341)	8.563 ₂₄ (3.341)	5.610 ₂₉ (2.470)	5.690 ₃₅ (2.470)	0.392 ₃₃ 20 ₇₁	0.059 ₃₂ 3 ₄₅
Jenson Button <i>GBR</i> (2000 bis 2006)	8.181 ₂₁ (3.233)	8.470 ₂₃ (3.236)	8.417 ₁₉ (3.236)	5.205 ₁₇ (2.392)	5.166 ₁₃ (2.392)	0.475 ₁₉ 57 ₂₀	0.008 ₇₀ 1 ₆₀
Richie Ginther <i>USA</i> (1960 bis 1966)	8.183 ₂₂ (3.349)	8.447 ₁₉ (3.351)	8.528 ₂₁ (3.351)	5.963 ₅₇ (2.477)	6.022 ₆₁ (2.477)	0.519 ₁₅ 28 ₅₉	0.019 ₅₆ 1 ₆₀
Erik Comas <i>FRA</i> (1991 bis 1994)	8.202 ₂₃ (3.300)	8.468 ₂₂ (3.303)	8.458 ₂₀ (3.302)	5.660 ₃₄ (2.441)	5.653 ₃₀ (2.441)	0.095 ₁₀₂ 61 ₀₄	0.000 ₇₄ 0 ₇₄
Maurice Trintignant <i>FRA</i> (1950 bis 1964)	8.212 ₂₄ (3.303)	8.501 ₂₄ (3.305)	8.639 ₂₉ (3.307)	5.703 ₃₇ (2.444)	5.805 ₄₇ (2.445)	0.238 ₇₀ 20 ₇₁	0.024 ₄₉ 2 ₅₂
Denny Hulme <i>NZL</i> (1965 bis 1974)	8.243 ₂₅ (3.264)	8.505 ₂₅ (3.266)	8.593 ₂₆ (3.267)	5.247 ₁₈ (2.415)	5.312 ₁₈ (2.415)	0.545 ₁₁ 61 ₁₆	0.071 ₂₇ 8 ₂₈
Ayrton Senna <i>BRA</i> (1984 bis 1994)	8.257 ₂₆ (3.200)	8.562 ₂₉ (3.203)	8.579 ₂₅ (3.203)	5.593 ₂₇ (2.368)	5.606 ₂₆ (2.368)	0.593 ₇ 96 ₆	0.253 ₅ 41 ₃
Mark Webber <i>AUS</i> (2002 bis 2006)	8.269 ₂₇ (3.329)	8.547 ₂₆ (3.331)	8.532 ₂₂ (3.331)	5.432 ₂₁ (2.463)	5.421 ₂₁ (2.463)	0.284 ₅₉ 25 ₆₄	0.000 ₇₄ 0 ₇₄
Jean Behra <i>FRA</i> (1952 bis 1959)	8.280 ₂₈ (3.344)	8.582 ₃₀ (3.347)	8.737 ₃₉ (3.348)	5.767 ₄₅ (2.474)	5.881 ₅₁ (2.475)	0.302 ₅₄ 16 ₇₈	0.000 ₇₄ 0 ₇₄
François Cevert <i>FRA</i> (1970 bis 1973)	8.286 ₂₉ (3.412)	8.555 ₂₈ (3.414)	8.612 ₂₇ (3.414)	5.742 ₄₃ (2.524)	5.784 ₄₅ (2.524)	0.404 ₃₀ 19 ₇₅	0.021 ₅₃ 1 ₆₀
Harry Schell <i>USA</i> (1950 bis 1960)	8.298 ₃₀ (3.337)	8.550 ₂₇ (3.339)	8.690 ₃₅ (3.341)	5.779 ₄₇ (2.469)	5.882 ₅₂ (2.470)	0.211 ₇₅ 12 ₈₄	0.000 ₇₄ 0 ₇₄
Carlos Reutemann <i>ARG</i> (1972 bis 1982)	8.304 ₃₁ (3.230)	8.585 ₃₁ (3.232)	8.637 ₂₈ (3.232)	5.649 ₃₂ (2.390)	5.687 ₃₄ (2.390)	0.452 ₂₃ 66 ₁₄	0.082 ₂₃ 12 ₁₈
John Watson <i>GBR</i> (1973 bis 1985)	8.307 ₃₂ (3.228)	8.594 ₃₂ (3.231)	8.650 ₃₀ (3.231)	5.568 ₂₅ (2.388)	5.609 ₂₇ (2.388)	0.305 ₅₃ 47 ₃₄	0.032 ₄₆ 5 ₃₈
Chris Amon <i>NZL</i> (1963 bis 1976)	8.326 ₃₃ (3.271)	8.594 ₃₃ (3.273)	8.688 ₃₄ (3.273)	5.810 ₄₉ (2.420)	5.878 ₅₀ (2.420)	0.269 ₆₁ 29 ₅₅	0.000 ₇₄ 0 ₇₄
Mario Andretti <i>USA</i> (1968 bis 1982)	8.371 ₃₄ (3.235)	8.663 ₃₄ (3.237)	8.697 ₃₆ (3.237)	5.719 ₄₁ (2.393)	5.744 ₄₁ (2.393)	0.290 ₅₈ 38 ₄₆	0.092 ₁₉ 12 ₁₈
Damon Hill <i>GBR</i> (1992 bis 1999)	8.387 ₃₅ (3.211)	8.673 ₃₆ (3.213)	8.657 ₃₁ (3.213)	5.393 ₂₀ (2.375)	5.381 ₁₉ (2.375)	0.459 ₂₂ 56 ₂₄	0.180 ₈ 22 ₁₀
John Surtees <i>GBR</i> (1960 bis 1972)	8.387 ₃₆ (3.296)	8.673 ₃₇ (3.298)	8.753 ₄₁ (3.298)	5.704 ₃₈ (2.438)	5.762 ₄₃ (2.438)	0.354 ₄₀ 40 ₄₁	0.053 ₃₃ 6 ₃₂
Marc Surer <i>SUI</i> (1979 bis 1986)	8.409 ₃₇ (3.248)	8.663 ₃₅ (3.250)	8.723 ₃₈ (3.250)	6.001 ₆₂ (2.402)	6.045 ₆₃ (2.402)	0.125 ₉₂ 11 ₈₈	0.000 ₇₄ 0 ₇₄
Rubens Barrichello <i>BRA</i> (1993 bis 2006)	8.428 ₃₈ (3.192)	8.699 ₃₈ (3.194)	8.679 ₃₃ (3.194)	5.706 ₃₉ (2.361)	5.691 ₃₆ (2.361)	0.466 ₂₁ 110 ₄	0.038 ₃₉ 9 ₂₆
Mika Häkkinen <i>FIN</i> (1991 bis 2001)	8.442 ₃₉ (3.211)	8.706 ₃₉ (3.214)	8.678 ₃₂ (3.214)	5.676 ₃₅ (2.376)	5.656 ₃₁ (2.376)	0.503 ₁₆ 83 ₉	0.121 ₁₂ 20 ₁₁
Bruce McLaren <i>NZL</i> (1958 bis 1970)	8.449 ₄₀ (3.287)	8.711 ₄₀ (3.290)	8.816 ₄₅ (3.290)	5.620 ₃₁ (2.432)	5.697 ₃₈ (2.433)	0.481 ₁₈ 50 ₃₁	0.038 ₃₉ 4 ₄₂
Eddie Irvine <i>GBR</i> (1993 bis 2002)	8.480 ₄₁ (3.211)	8.749 ₄₂ (3.213)	8.716 ₃₇ (3.213)	5.685 ₃₆ (2.375)	5.661 ₃₃ (2.375)	0.338 ₄₆ 50 ₃₁	0.027 ₄₈ 4 ₄₂
Keke Rosberg <i>FIN</i> (1978 bis 1986)	8.484 ₄₂ (3.227)	8.739 ₄₁ (3.230)	8.760 ₄₂ (3.230)	5.719 ₄₀ (2.388)	5.735 ₃₉ (2.388)	0.297 ₅₇ 38 ₄₆	0.039 ₃₈ 5 ₃₈
Arturo Merzario <i>ITA</i> (1972 bis 1979)	8.516 ₄₃ (3.307)	8.796 ₄₄ (3.309)	8.834 ₄₇ (3.309)	5.849 ₅₁ (2.446)	5.877 ₄₉ (2.446)	0.060 ₁₁₃ 51 ₀₉	0.000 ₇₄ 0 ₇₄
David Coulthard <i>GBR</i> (1994 bis 2006)	8.522 ₄₄ (3.215)	8.795 ₄₃ (3.217)	8.753 ₄₀ (3.217)	5.903 ₅₃ (2.378)	5.872 ₄₈ (2.378)	0.542 ₁₂ 115 ₃	0.061 ₃₁ 13 ₁₇
Jacques Laffite <i>FRA</i> (1974 bis 1986)	8.530 ₄₅ (3.217)	8.806 ₄₆ (3.219)	8.826 ₄₆ (3.219)	5.939 ₅₆ (2.380)	5.954 ₅₅ (2.380)	0.328 ₅₀ 59 ₁₇	0.033 ₄₅ 6 ₃₂
Jacques Villeneuve <i>CAN</i> (1996 bis 2006)	8.533 ₄₆ (3.207)	8.814 ₄₇ (3.209)	8.775 ₄₃ (3.209)	5.609 ₂₈ (2.372)	5.580 ₂₅ (2.372)	0.321 ₅₁ 53 ₂₇	0.067 ₂₈ 11 ₂₁

REINER EICHENBERGER AND DAVID STADELMANN

Jack Brabham <i>AUS</i> (1955 bis 1970)	8.535 ₄₇ (3.265)	8.798 ₄₅ (3.267)	8.908 ₅₁ (3.268)	5.579 ₂₆ (2.415)	5.660 ₃₂ (2.416)	0.414 ₂₆ 53 ₂₇	0.109 ₁₄ 14 ₁₄
Nelson Piquet <i>BRA</i> (1978 bis 1991)	8.566 ₄₈ (3.191)	8.865 ₄₉ (3.194)	8.881 ₅₀ (3.194)	5.743 ₄₄ (2.361)	5.755 ₄₂ (2.361)	0.483 ₁₇ 100 ₅	0.111 ₁₃ 23 ₉
Roy Salvadori <i>GBR</i> (1952 bis 1962)	8.588 ₄₉ (3.341)	8.909 ₅₂ (3.344)	9.036 ₅₆ (3.345)	5.900 ₅₂ (2.472)	5.993 ₅₈ (2.473)	0.140 ₈₉ 7 ₁₀₁	0.000 ₇₄ 0 ₇₄
Juan Pablo Montoya <i>COL</i> (2001 bis 2006)	8.599 ₅₀ (3.249)	8.849 ₄₈ (3.251)	8.796 ₄₄ (3.251)	5.493 ₂₄ (2.403)	5.455 ₂₂ (2.404)	0.600 ₅ 57 ₂₀	0.074 ₂₆ 7 ₃₀
H.-H. Frentzen <i>GER</i> (1994 bis 2003)	8.612 ₅₁ (3.197)	8.907 ₅₁ (3.200)	8.874 ₄₉ (3.200)	5.656 ₃₃ (2.366)	5.632 ₂₈ (2.366)	0.350 ₄₂ 56 ₂₄	0.019 ₅₆ 3 ₄₅
Alan Jones <i>AUS</i> (1975 bis 1986)	8.616 ₅₂ (3.241)	8.877 ₅₀ (3.244)	8.923 ₅₂ (3.244)	6.014 ₆₃ (2.398)	6.048 ₆₅ (2.398)	0.333 ₄₇ 39 ₄₄	0.103 ₁₆ 12 ₁₈
Mika Salo <i>FIN</i> (1994 bis 2002)	8.641 ₅₃ (3.231)	8.909 ₅₃ (3.233)	8.869 ₄₈ (3.233)	5.932 ₅₄ (2.390)	5.902 ₅₃ (2.390)	0.144 ₈₇ 16 ₇₈	0.000 ₇₄ 0 ₇₄
Thierry Boutsen <i>BEL</i> (1983 bis 1993)	8.644 ₅₄ (3.200)	8.927 ₅₄ (3.202)	8.953 ₅₄ (3.202)	6.062 ₆₇ (2.367)	6.081 ₆₇ (2.367)	0.250 ₆₇ 41 ₄₀	0.018 ₅₉ 3 ₄₅
Mark Blundell <i>GBR</i> (1991 bis 1995)	8.680 ₅₅ (3.252)	8.953 ₅₅ (3.254)	8.925 ₅₃ (3.254)	6.067 ₆₉ (2.406)	6.047 ₆₄ (2.406)	0.206 ₇₆ 13 ₈₃	0.000 ₇₄ 0 ₇₄
Jean Alesi <i>FRA</i> (1989 bis 2001)	8.698 ₅₆ (3.155)	8.993 ₅₆ (3.158)	8.983 ₅₅ (3.158)	5.977 ₆₀ (2.334)	5.969 ₅₇ (2.334)	0.347 ₄₃ 70 ₁₃	0.005 ₇₃ 1 ₆₀
H. J. Stuck <i>GER</i> (1974 bis 1979)	8.727 ₅₇ (3.277)	9.012 ₅₇ (3.280)	9.065 ₅₉ (3.280)	5.972 ₅₉ (2.425)	6.011 ₅₉ (2.425)	0.148 ₈₆ 12 ₈₄	0.000 ₇₄ 0 ₇₄
Innes Ireland <i>GBR</i> (1959 bis 1966)	8.759 ₅₈ (3.326)	9.047 ₅₉ (3.329)	9.162 ₆₆ (3.329)	6.072 ₇₀ (2.461)	6.157 ₇₁ (2.461)	0.264 ₆₂ 14 ₈₁	0.019 ₅₆ 1 ₆₀
Martin Brundle <i>GBR</i> (1984 bis 1996)	8.772 ₅₉ (3.182)	9.046 ₅₈ (3.185)	9.051 ₅₈ (3.184)	6.064 ₆₈ (2.354)	6.068 ₆₆ (2.354)	0.236 ₇₁ 39 ₄₄	0.000 ₇₄ 0 ₇₄
Riccardo Patrese <i>ITA</i> (1977 bis 1993)	8.787 ₆₀ (3.188)	9.068 ₆₀ (3.190)	9.084 ₆₀ (3.190)	6.176 ₇₄ (2.358)	6.188 ₇₄ (2.358)	0.284 ₅₉ 73 ₁₁	0.023 ₅₁ 6 ₃₂
Niki Lauda <i>AUT</i> (1971 bis 1985)	8.806 ₆₁ (3.212)	9.078 ₆₁ (3.214)	9.123 ₆₂ (3.215)	5.618 ₃₀ (2.376)	5.651 ₂₉ (2.376)	0.412 ₂₇ 73 ₁₁	0.141 ₁₁ 25 ₆
Felipe Massa <i>BRA</i> (2002 bis 2006)	8.812 ₆₂ (3.248)	9.084 ₆₂ (3.250)	9.037 ₅₇ (3.250)	5.731 ₄₂ (2.403)	5.696 ₃₇ (2.403)	0.352 ₄₁ 25 ₆₄	0.028 ₄₇ 2 ₅₂
Vittorio Brambilla <i>ITA</i> (1974 bis 1980)	8.830 ₆₃ (3.305)	9.120 ₆₃ (3.307)	9.174 ₆₈ (3.307)	6.057 ₆₆ (2.445)	6.097 ₆₉ (2.445)	0.114 ₉₆ 9 ₉₄	0.013 ₆₅ 1 ₆₀
J. P. Beltoise <i>FRA</i> (1967 bis 1974)	8.848 ₆₄ (3.272)	9.124 ₆₄ (3.274)	9.206 ₇₁ (3.275)	5.964 ₅₈ (2.421)	6.024 ₆₂ (2.421)	0.299 ₅₅ 26 ₆₂	0.011 ₆₇ 1 ₆₀
Jochen Mass <i>GER</i> (1973 bis 1982)	8.863 ₆₅ (3.244)	9.139 ₆₅ (3.247)	9.176 ₇₀ (3.247)	6.348 ₈₃ (2.400)	6.375 ₈₄ (2.400)	0.246 ₆₈ 28 ₅₉	0.009 ₆₈ 1 ₆₀
Jarno Trulli <i>ITA</i> (1997 bis 2006)	8.869 ₆₆ (3.206)	9.148 ₆₆ (3.208)	9.105 ₆₁ (3.208)	5.837 ₅₀ (2.372)	5.805 ₄₆ (2.372)	0.299 ₅₅ 50 ₃₁	0.006 ₇₁ 1 ₆₀
Ralf Schumacher <i>GER</i> (1997 bis 2006)	8.870 ₆₇ (3.217)	9.159 ₆₇ (3.220)	9.124 ₆₃ (3.220)	5.806 ₄₈ (2.380)	5.780 ₄₄ (2.380)	0.527 ₁₃ 87 ₈	0.036 ₄₂ 6 ₃₂
Mike Hailwood <i>GBR</i> (1963 bis 1974)	8.883 ₆₈ (3.288)	9.170 ₆₉ (3.291)	9.235 ₇₃ (3.291)	6.134 ₇₂ (2.433)	6.182 ₇₃ (2.433)	0.200 ₇₇ 10 ₉₁	0.000 ₇₄ 0 ₇₄
Giancarlo Fisichella <i>ITA</i> (1996 bis 2006)	8.892 ₆₉ (3.235)	9.171 ₇₀ (3.237)	9.136 ₆₄ (3.237)	5.769 ₄₆ (2.393)	5.743 ₄₀ (2.393)	0.363 ₃₈ 65 ₁₅	0.017 ₆₂ 3 ₄₅
Stefan Johansson <i>SWE</i> (1983 bis 1991)	8.892 ₇₀ (3.233)	9.164 ₆₈ (3.235)	9.159 ₆₅ (3.235)	5.938 ₅₅ (2.392)	5.935 ₅₄ (2.392)	0.252 ₆₆ 26 ₆₂	0.000 ₇₄ 0 ₇₄
Eddie Cheever <i>USA</i> (1978 bis 1989)	8.903 ₇₁ (3.218)	9.196 ₇₃ (3.221)	9.222 ₇₂ (3.221)	6.279 ₇₈ (2.381)	6.298 ₇₈ (2.381)	0.175 ₈₃ 25 ₆₄	0.000 ₇₄ 0 ₇₄
Ukyo Katayama <i>JPN</i> (1992 bis 1997)	8.925 ₇₂ (3.238)	9.195 ₇₂ (3.240)	9.171 ₆₇ (3.240)	6.367 ₈₄ (2.395)	6.350 ₈₁ (2.395)	0.031 ₁₂₁ 3 ₁₁₉	0.000 ₇₄ 0 ₇₄
Jo Bonnier <i>SWE</i> (1957 bis 1971)	8.930 ₇₃ (3.278)	9.187 ₇₁ (3.280)	9.298 ₇₅ (3.281)	6.179 ₇₅ (2.425)	6.261 ₇₇ (2.425)	0.185 ₇₉ 20 ₇₁	0.009 ₆₈ 1 ₆₀
Alexander Wurz <i>AUT</i> (1997 bis 2005)	8.956 ₇₄ (3.307)	9.228 ₇₄ (3.309)	9.176 ₆₉ (3.310)	5.996 ₆₁ (2.447)	5.958 ₅₆ (2.447)	0.141 ₈₈ 11 ₈₈	0.000 ₇₄ 0 ₇₄
Ivan Capelli <i>ITA</i> (1985 bis 1993)	8.988 ₇₅ (2.967)	9.272 ₇₅ (2.969)	9.275 ₇₄ (2.969)	6.016 ₆₄ (2.195)	6.019 ₆₀ (2.195)	0.122 ₉₅ 12 ₈₄	0.000 ₇₄ 0 ₇₄

WHO IS THE BEST FORMULA 1 DRIVER? AN ECONOMIC APPROACH TO EVALUATING TALENT

Carlos Pace <i>BRA</i> (1972 bis 1977)	8.989 ₇₆ (3.277)	9.274 ₇₆ (3.280)	9.340 ₇₆ (3.280)	6.055 ₆₅ (2.425)	6.103 ₇₀ (2.425)	0.219 ₇₂ 16 ₇₈	0.014 ₆₄ 1 ₆₀
Clay Regazzoni <i>SUI</i> (1970 bis 1980)	9.077 ₇₇ (3.230)	9.337 ₇₇ (3.232)	9.383 ₇₇ (3.232)	6.187 ₇₆ (2.389)	6.221 ₇₆ (2.389)	0.374 ₃₇ 52 ₃₀	0.036 ₄₂ 5 ₃₈
Jo Siffert <i>SUI</i> (1962 bis 1971)	9.089 ₇₈ (3.263)	9.352 ₇₈ (3.265)	9.453 ₈₀ (3.265)	6.289 ₇₉ (2.414)	6.363 ₈₂ (2.414)	0.200 ₇₇ 20 ₇₁	0.020 ₅₅ 2 ₅₂
Olivier Panis <i>FRA</i> (1994 bis 2004)	9.141 ₇₉ (3.212)	9.417 ₇₉ (3.215)	9.388 ₇₈ (3.215)	6.114 ₇₁ (2.376)	6.093 ₆₈ (2.376)	0.182 ₈₁ 29 ₅₅	0.006 ₇₁ 1 ₆₀
Nigel Mansell <i>GBR</i> (1980 bis 1995)	9.186 ₈₀ (3.196)	9.464 ₈₀ (3.199)	9.476 ₈₂ (3.199)	6.161 ₇₃ (2.365)	6.170 ₇₂ (2.365)	0.429 ₂₅ 82 ₁₀	0.162 ₁₀ 31 ₄
Gerhard Berger <i>AUT</i> (1984 bis 1997)	9.192 ₈₁ (3.177)	9.467 ₈₂ (3.179)	9.464 ₈₁ (3.179)	6.474 ₈₅ (2.350)	6.472 ₈₅ (2.350)	0.448 ₂₄ 94 ₇	0.048 ₃₄ 10 ₂₂
Johnny Herbert <i>GBR</i> (1989 bis 2000)	9.201 ₈₂ (3.189)	9.466 ₈₁ (3.192)	9.446 ₇₉ (3.191)	6.232 ₇₇ (2.359)	6.218 ₇₅ (2.359)	0.176 ₈₂ 29 ₅₅	0.018 ₅₉ 3 ₄₅
Teo Fabi <i>ITA</i> (1982 bis 1987)	9.204 ₈₃ (3.249)	9.474 ₈₃ (3.251)	9.480 ₈₃ (3.251)	6.311 ₈₁ (2.404)	6.315 ₇₉ (2.404)	0.127 ₉₁ 9 ₉₄	0.000 ₇₄ 0 ₇₄
Mauricio Gugelmin <i>BRA</i> (1988 bis 1992)	9.260 ₈₄ (3.054)	9.546 ₈₄ (3.057)	9.534 ₈₄ (3.056)	6.339 ₈₂ (2.260)	6.330 ₈₀ (2.260)	0.050 ₁₁₈ 4 ₁₁₆	0.000 ₇₄ 0 ₇₄
Jos Verstappen <i>NED</i> (1994 bis 2003)	9.362 ₈₅ (3.259)	9.613 ₈₅ (3.261)	9.571 ₈₅ (3.261)	6.530 ₈₇ (2.411)	6.499 ₈₆ (2.411)	0.065 ₁₁₂ 7 ₁₀₁	0.000 ₇₄ 0 ₇₄
Philippe Streiff <i>FRA</i> (1984 bis 1988)	9.396 ₈₆ (3.295)	9.652 ₈₆ (3.297)	9.632 ₈₇ (3.297)	6.664 ₉₁ (2.437)	6.649 ₉₂ (2.437)	0.093 ₁₀₄ 5 ₁₀₉	0.000 ₇₄ 0 ₇₄
Christian Klien <i>AUT</i> (2004 bis 2006)	9.407 ₈₇ (3.317)	9.653 ₈₇ (3.319)	9.599 ₈₆ (3.319)	6.617 ₉₀ (2.453)	6.578 ₈₉ (2.453)	0.154 ₈₅ 8 ₉₇	0.000 ₇₄ 0 ₇₄
Jackie Oliver <i>GBR</i> (1968 bis 1977)	9.473 ₈₈ (3.328)	9.763 ₈₉ (3.330)	9.847 ₉₀ (3.330)	6.311 ₈₀ (2.462)	6.373 ₈₃ (2.462)	0.098 ₁₀₀ 5 ₁₀₉	0.000 ₇₄ 0 ₇₄
Philippe Alliot <i>FRA</i> (1984 bis 1994)	9.498 ₈₉ (3.245)	9.742 ₈₈ (3.246)	9.741 ₈₈ (3.246)	6.520 ₈₆ (2.400)	6.519 ₈₇ (2.400)	0.052 ₁₁₇ 6 ₁₀₄	0.000 ₇₄ 0 ₇₄
Nicola Larini <i>ITA</i> (1987 bis 1997)	9.523 ₉₀ (3.305)	9.782 ₉₀ (3.307)	9.777 ₈₉ (3.306)	6.801 ₉₇ (2.444)	6.797 ₉₇ (2.444)	0.027 ₁₂₂ 2 ₁₂₂	0.000 ₇₄ 0 ₇₄
Lorenzo Bandini <i>ITA</i> (1961 bis 1967)	9.556 ₉₁ (3.355)	9.836 ₉₁ (3.358)	9.896 ₉₃ (3.358)	6.883 ₁₀₁ (2.482)	6.928 ₁₀₂ (2.482)	0.405 ₂₉ 17 ₇₇	0.024 ₄₉ 1 ₆₀
Pedro Diniz <i>ESP</i> (1995 bis 2000)	9.616 ₉₂ (3.223)	9.889 ₉₃ (3.225)	9.855 ₉₁ (3.225)	6.670 ₉₃ (2.384)	6.645 ₉₁ (2.384)	0.081 ₁₀₆ 8 ₉₇	0.000 ₇₄ 0 ₇₄
Manfred Winkelhock <i>GER</i> (1982 bis 1985)	9.620 ₉₃ (3.403)	9.866 ₉₂ (3.405)	9.859 ₉₂ (3.405)	6.931 ₁₀₂ (2.517)	6.926 ₁₀₁ (2.517)	0.018 ₁₂₃ 1 ₁₂₃	0.000 ₇₄ 0 ₇₄
Patrick Tambay <i>FRA</i> (1977 bis 1986)	9.738 ₉₄ (3.218)	9.999 ₉₄ (3.220)	10.020 ₉₄ (3.220)	6.714 ₉₄ (2.381)	6.732 ₉₄ (2.381)	0.260 ₆₄ 32 ₅₁	0.016 ₆₃ 2 ₅₂
Derek Warwick <i>GBR</i> (1981 bis 1993)	9.761 ₉₅ (3.216)	10.050 ₉₆ (3.219)	10.070 ₉₇ (3.219)	6.862 ₁₀₀ (2.380)	6.878 ₁₀₀ (2.380)	0.185 ₇₉ 30 ₅₄	0.000 ₇₄ 0 ₇₄
Michele Alboreto <i>ITA</i> (1981 bis 1994)	9.770 ₉₆ (3.200)	10.034 ₉₅ (3.201)	10.030 ₉₅ (3.201)	6.743 ₉₅ (2.367)	6.741 ₉₅ (2.367)	0.219 ₇₂ 47 ₃₄	0.023 ₅₁ 5 ₃₈
Jonathan Palmer <i>GBR</i> (1983 bis 1989)	9.780 ₉₇ (3.278)	10.057 ₉₇ (3.280)	10.050 ₉₆ (3.280)	7.020 ₁₀₇ (2.425)	7.014 ₁₀₆ (2.424)	0.091 ₁₀₅ 8 ₉₇	0.000 ₇₄ 0 ₇₄
Jody Scheckter <i>SAF</i> (1972 bis 1980)	9.831 ₉₈ (3.286)	10.113 ₉₈ (3.288)	10.160 ₉₉ (3.288)	6.666 ₉₂ (2.431)	6.704 ₉₃ (2.431)	0.469 ₂₀ 53 ₂₇	0.088 ₂₀ 10 ₂₂
Andrea de Cesaris <i>ITA</i> (1980 bis 1994)	9.869 ₉₉ (3.195)	10.137 ₉₉ (3.197)	10.150 ₉₈ (3.197)	6.836 ₉₉ (2.364)	6.845 ₉₉ (2.364)	0.103 ₉₉ 22 ₆₇	0.000 ₇₄ 0 ₇₄
Stefano Modena <i>ITA</i> (1987 bis 1992)	9.897 ₁₀₀ (3.203)	10.159 ₁₀₀ (3.206)	10.160 ₁₀₀ (3.206)	6.576 ₈₉ (2.370)	6.575 ₈₈ (2.370)	0.074 ₁₀₈ 6 ₁₀₄	0.000 ₇₄ 0 ₇₄
Eric Bernard <i>FRA</i> (1989 bis 1994)	9.915 ₁₀₁ (3.309)	10.192 ₁₀₁ (3.311)	10.210 ₁₀₁ (3.311)	6.806 ₉₈ (2.448)	6.817 ₉₈ (2.448)	0.106 ₉₈ 5 ₁₀₉	0.000 ₇₄ 0 ₇₄
Alex Caffi <i>ITA</i> (1986 bis 1991)	9.973 ₁₀₂ (3.332)	10.260 ₁₀₂ (3.334)	10.260 ₁₀₂ (3.334)	6.748 ₉₆ (2.465)	6.750 ₉₆ (2.465)	0.040 ₁₂₀ 3 ₁₁₉	0.000 ₇₄ 0 ₇₄
Bruno Giacomelli <i>ITA</i> (1977 bis 1983)	10.010 ₁₀₃ (3.253)	10.275 ₁₀₃ (3.255)	10.300 ₁₀₃ (3.255)	6.969 ₁₀₄ (2.406)	6.986 ₁₀₄ (2.406)	0.073 ₁₀₉ 6 ₁₀₄	0.000 ₇₄ 0 ₇₄
Rolf Stommelen <i>GER</i> (1970 bis 1978)	10.020 ₁₀₄ (3.269)	10.290 ₁₀₄ (3.271)	10.360 ₁₀₄ (3.271)	7.006 ₁₀₆ (2.418)	7.055 ₁₀₇ (2.418)	0.113 ₉₇ 7 ₁₀₁	0.000 ₇₄ 0 ₇₄

Pierluigi Martini <i>ITA</i> (1985 bis 1995)	10.120 ₁₀₅ (3.277)	10.385 ₁₀₅ (3.278)	10.390 ₁₀₅ (3.278)	7.225 ₁₁₂ (2.424)	7.229 ₁₁₂ (2.424)	0.081 ₁₀₆ 10 ₉₁	0.000 ₇₄ 0 ₇₄
René Arnoux <i>FRA</i> (1978 bis 1989)	10.160 ₁₀₆ (3.212)	10.431 ₁₀₆ (3.215)	10.450 ₁₀₆ (3.214)	6.969 ₁₀₅ (2.376)	6.982 ₁₀₃ (2.376)	0.256 ₆₅ 42 ₃₈	0.043 ₃₆ 7 ₃₀
Patrick Depailler <i>FRA</i> (1972 bis 1980)	10.170 ₁₀₇ (3.262)	10.431 ₁₀₇ (3.264)	10.490 ₁₀₈ (3.264)	6.947 ₁₀₃ (2.413)	6.988 ₁₀₅ (2.413)	0.379 ₃₅ 36 ₄₈	0.021 ₅₃ 2 ₅₂
Tom Pryce <i>GBR</i> (1974 bis 1977)	10.170 ₁₀₈ (3.374)	10.448 ₁₀₈ (3.376)	10.460 ₁₀₇ (3.376)	6.574 ₈₈ (2.496)	6.582 ₉₀ (2.496)	0.214 ₇₄ 9 ₉₄	0.000 ₇₄ 0 ₇₄
J. P. Jarier <i>FRA</i> (1971 bis 1983)	10.300 ₁₀₉ (3.275)	10.549 ₁₀₉ (3.277)	10.570 ₁₀₉ (3.277)	7.204 ₁₁₁ (2.423)	7.223 ₁₁₁ (2.423)	0.098 ₁₀₀ 14 ₈₁	0.000 ₇₄ 0 ₇₄
Pedro delaRosa <i>ESP</i> (1999 bis 2006)	10.420 ₁₁₀ (3.271)	10.676 ₁₁₀ (3.273)	10.640 ₁₁₀ (3.273)	7.560 ₁₁₅ (2.420)	7.531 ₁₁₅ (2.420)	0.131 ₉₀ 11 ₈₈	0.000 ₇₄ 0 ₇₄
Bertrand Gachot <i>FRA</i> (1989 bis 1995)	10.440 ₁₁₁ (3.329)	10.696 ₁₁₁ (3.330)	10.680 ₁₁₁ (3.330)	7.177 ₁₁₀ (2.462)	7.163 ₁₁₀ (2.462)	0.048 ₁₁₉ 4 ₁₁₆	0.000 ₇₄ 0 ₇₄
Gilles Villeneuve <i>CAN</i> (1977 bis 1982)	10.570 ₁₁₂ (3.287)	10.839 ₁₁₂ (3.289)	10.870 ₁₁₂ (3.289)	7.046 ₁₀₈ (2.432)	7.065 ₁₀₈ (2.432)	0.309 ₅₂ 21 ₆₉	0.088 ₂₀ 6 ₃₂
Piercarlo Ghinzani <i>ITA</i> (1981 bis 1989)	10.630 ₁₁₃ (3.315)	10.900 ₁₁₃ (3.317)	10.910 ₁₁₄ (3.317)	7.103 ₁₀₉ (2.452)	7.112 ₁₀₉ (2.452)	0.009 ₁₂₄ 1 ₁₂₃	0.000 ₇₄ 0 ₇₄
Derek Daly <i>IRL</i> (1978 bis 1982)	10.690 ₁₁₄ (3.337)	10.909 ₁₁₄ (3.339)	10.910 ₁₁₃ (3.338)	7.570 ₁₁₆ (2.468)	7.572 ₁₁₆ (2.468)	0.125 ₉₂ 8 ₉₇	0.000 ₇₄ 0 ₇₄
Roberto Moreno <i>BRA</i> (1987 bis 1995)	10.730 ₁₁₅ (3.299)	10.992 ₁₁₅ (3.301)	10.990 ₁₁₆ (3.301)	7.282 ₁₁₃ (2.440)	7.278 ₁₁₃ (2.440)	0.067 ₁₁₁ 5 ₁₀₉	0.000 ₇₄ 0 ₇₄
Gianni Morbidelli <i>ITA</i> (1990 bis 1997)	10.780 ₁₁₆ (3.323)	11.018 ₁₁₆ (3.324)	10.990 ₁₁₅ (3.324)	7.891 ₁₂₁ (2.458)	7.872 ₁₂₀ (2.458)	0.071 ₁₁₀ 5 ₁₀₉	0.000 ₇₄ 0 ₇₄
J. J. Lehto <i>FIN</i> (1989 bis 1994)	10.830 ₁₁₇ (3.264)	11.063 ₁₁₇ (3.265)	11.050 ₁₁₇ (3.265)	7.713 ₁₁₉ (2.414)	7.702 ₁₁₉ (2.414)	0.057 ₁₁₄ 4 ₁₁₆	0.000 ₇₄ 0 ₇₄
Henri Pescarolo <i>FRA</i> (1968 bis 1976)	10.970 ₁₁₈ (3.283)	11.232 ₁₁₉ (3.285)	11.320 ₁₁₉ (3.285)	7.932 ₁₂₂ (2.428)	7.995 ₁₂₂ (2.429)	0.095 ₁₀₂ 6 ₁₀₄	0.000 ₇₄ 0 ₇₄
J. P. Jabouille <i>FRA</i> (1975 bis 1981)	10.990 ₁₁₉ (3.351)	11.222 ₁₁₈ (3.352)	11.270 ₁₁₈ (3.352)	8.059 ₁₂₄ (2.478)	8.091 ₁₂₄ (2.478)	0.054 ₁₁₆ 3 ₁₁₉	0.036 ₄₂ 2 ₅₂
Didier Pironi <i>FRA</i> (1978 bis 1982)	11.060 ₁₂₀ (3.275)	11.320 ₁₂₀ (3.277)	11.340 ₁₂₁ (3.277)	7.865 ₁₂₀ (2.422)	7.881 ₁₂₁ (2.422)	0.403 ₃₁ 29 ₅₅	0.042 ₃₇ 3 ₄₅
Satoru Nakajima <i>JPN</i> (1987 bis 1991)	11.070 ₁₂₁ (3.213)	11.328 ₁₂₁ (3.215)	11.330 ₁₂₀ (3.215)	7.633 ₁₁₈ (2.377)	7.635 ₁₁₈ (2.377)	0.125 ₉₂ 10 ₉₁	0.000 ₇₄ 0 ₇₄
Takuma Sato <i>JPN</i> (2002 bis 2006)	11.220 ₁₂₂ (3.313)	11.471 ₁₂₂ (3.314)	11.400 ₁₂₂ (3.315)	8.058 ₁₂₃ (2.450)	8.008 ₁₂₃ (2.450)	0.169 ₈₄ 12 ₈₄	0.000 ₇₄ 0 ₇₄
Alessandro Nannini <i>ITA</i> (1986 bis 1990)	11.250 ₁₂₃ (3.255)	11.518 ₁₂₃ (3.257)	11.530 ₁₂₃ (3.257)	7.369 ₁₁₄ (2.408)	7.378 ₁₁₄ (2.408)	0.244 ₆₉ 19 ₇₅	0.013 ₆₅ 1 ₆₀
Aguri Suzuki <i>JPN</i> (1988 bis 1995)	11.390 ₁₂₄ (3.262)	11.659 ₁₂₄ (3.264)	11.670 ₁₂₄ (3.264)	7.616 ₁₁₇ (2.413)	7.622 ₁₁₇ (2.413)	0.057 ₁₁₄ 5 ₁₀₉	0.000 ₇₄ 0 ₇₄

Source: own calculations based on FORIX Data from 1950 to 2006. The indices represent the ranking within a column.

4.1. Superstars

According to specification (1) the TOP-10 drivers are: Juan Manuel Fangio (active between 1950 until 1958), Jim Clark (1960-1968), Michael Schumacher (1991-2006), Jackie Stewart (1965-1973), Mike Hawthorn (1952-1958), Fernando Alonso (since 2001), Alain Prost (1980-1993), Graham Hill (1958-1975), Emerson Fittipaldi (1970-1980), and Jacky Ickx (1967-1979).

All these drivers have won at least one championship during their career, apart from Jacky Ickx. Michael Schumacher, Juan Manuel Fangio and Alain Prost have won seven, five, and four world championships, respectively. Moreover, the ranking contains at least one driver of each era of Formula 1 driving.

The general trend of the ranking indicates that drivers from the earlier years of Formula 1 racing do generally better than more recent drivers. There are several reasons for this trend.

Drivers from the early ages of Formula 1 racing simply excelled. They were competing during their times against very strong competitors and won against these. In the old days, Formula 1 racing was an even more dangerous sport than it is today. Next to the former heroes from the early days of Formula 1 racing there are only a few recent stars such as Alain Prost and Michael Schumacher. Another recent star is Fernando Alonso ranked 6 and Kimi Räikkönen ranked 11. From Australia Mark Webber clearly deserves to be mentioned on rank 27. Young drivers in 2007 and 2008 such as Lewis Hamilton, Robert Kubica, Heikki Kovalainen und Nico Rosberg could not yet be ranked as they are not yet for a sufficiently long time period actively participating in Formula 1.

The best racer in history, Juan Manuel Fangio, is not only the best concerning our talent ranking of column (1) in *Table 1*. He is also the best when considering relative measures of races in points and wins as shown in columns (6) and (7). Juan Manuel Fangio has achieved point ranks in 84.3 % of the races he participated in and in 47.1 % of his races he actually won. Thus, out of the 51 races he participated in, he won 24, was 35 times on the podium and all of his dropouts were due to technical reasons. Thus, Juan Manuel Fangio is also the best driver when considering only relative measures. Moreover, he competed during his time against well-known and fast Formula 1 racers including Nino Farina, Sterling Moss and Alberto Ascari.⁹ Many of these strong competitors were outperformed by Juan Manuel Fangio on the same car.¹⁰

Michael Schumacher cannot be found in any of the estimated specifications on the first rank. In our preferred specification he ranks third. Usually, he scores second or worse. However, he is the best driver of the last three decades. Comparing coefficients between Juan Manuel Fangio and Michael Schumacher does not lead to significant results.

Some readers might be surprised by Jim Clark's excellent ranking. He ranks as second. His relative successes, i.e. races in points, podium positions over races, wins over races etc. lag slightly behind the achievements of Michael Schumacher. Jim Clark also dropped out often (28 of 72 participates) but his dropouts were usually due to technical problems. Whenever his car did not break down, he was very successful. Moreover, Jim Clark was successful against strong competitors such as Stirling Moss, Bruce McLaren, and Graham Hill.

Jackie Stewart clearly deserves rank 4 according to our preferred specification. He has been a world champion three times. His ranking is robust to numerous tests and he has been the best driver of his era.

When comparing coefficients using Wald-Tests for the TOP-10 drivers, they are not significantly different at the 5-%-level.¹¹ Comparisons become more significant if coefficient differences increase and when drivers of the same period are compared. Thus, Juan Manuel

⁹ Nino Farina and Alberto Ascari are not listed in *Table 1* as they were participating in fewer than 40 races. In an extended list Nino Farina (with 33 starts) and Alberto Ascari (with 32 starts) would have achieved the outstanding ranking of sixth and twelfth, respectively. Rankings which include drivers with more than 30 races show only minor changes to the results presented here, apart from Nino Farina and Alberto Ascari.

¹⁰ The title for the best constructors, i.e. for the best team, was first awarded in 1958 to Vanwall. Thus, it may be assumed that there were no "Pro-Fangio-Team Orders".

¹¹ We test the hypothesis of the "coefficient of driver I" minus the "coefficient of driver j" equals 0. At the 10-%-level Juan Manuel Fangio is significantly different from Graham Hill, Emerson Fittipaldi, and Jacky Ickx. All other drivers are not significantly different in pair wise comparisons.

Fangio is not THE best driver in history. Similarly, Jim Clark is not THE second-best and Michael Schumacher not THE third-best. Every era has its superstar. An analytical comparison for the whole period of Formula 1 racing shows that there are only minor differences between the top drivers. Moreover, there is a strong concentration between the ten top drivers. The list of the TOP-10 remains stable and is robust to changes in the specification of the estimation equations.

4.2. *New Insights*

Specialists in Formula 1 can possibly agree to the ranking proposed but the ranking also raises a number of questions.

Why is Michael Schumacher not the best? During his career, Michael Schumacher usually had very good racing cars. The exception to this can only be found at the beginning of his career. His relative measures for wins and races in points are worse than those of Juan Manuel Fangio. Clearly, Michael Schumacher has won against his competitors but he would have had more difficulty against competitors faced by Juan Manuel Fangio or Jim Clark. Additionally, his high number of wins must be compared to his far higher number of participations.¹² No tested specification shows that Michael Schumacher is the best. Moreover, his talent coefficient is not statistically significant from other younger stars such as Fernando Alonso (p-value = 0.586; F-value of Wald-Test 0.297) and Kimi Räikkönen (p-value = 0.155; F-value of Wald-Test = 2.024).

Why is Alain Prost better than Ayrton Senna? Many emotions are linked to Ayrton Senna and his early death. In the ranking presented, Ayrton Senna scores 25th. He is statistically significantly (p-value = 0.091; F-value of Wald-Test 2.845) lagging behind his great rival Alain Prost who scores seventh. The reason cannot be found in speed differences between the two drivers but rather in Ayrton Senna's relative instability. Alain Prost was stable and he drove successfully and achieved excellent classifications. In 202 races he dropped out 53 times due to technical problems and 11 times (5.4 %) due to human dropouts. This strikingly contrasts with Ayrton Senna. In 162 races, he was dropping out technically 50 times and 14 times (8.6 %) due to human reasons out of a total of 162 races.

How do more recent stars rank? The ranking of more recent superstars is very intuitive as shown in *Table 1* for the period up to 2006. Michael Schumacher is first followed by Fernando Alonso and Kimi Räikkönen. Nick Heidfeld ranks 16th. The list of ranked drivers shows that Jenson Button (21) and Mark Webber (27) are better than Rubens Barrichello (38), David Coulthard (44), Felipe Massa (62), Jarno Trulli (66), Ralf Schumacher (67), and Jancarlo Fisichella (69). But these drivers are actually doing better than some older world champions, such as Nigel Mansell (80) and Jody Scheckter (98). These champions were mainly champions thanks to their great cars. However, the more recent drivers are lagging behind the old stars as far as relative successes are concerned. Kimi Räikkönen only won 8.6 % of his races while Juan Manuel Fangio won almost 50 % and Michael Schumacher and Jim Clark approximately 35 %. Fernando Alonso has won 17 % of the races he participated in which

¹² Michael Schumacher participated in 250 races and started 248 times. With 257 starts Riccardo Patrese participated most often in Formula 1 history.

partly explains his talent coefficient. Sometimes the comparison between old and young is difficult. The number of technical dropouts has decreased over time. Thus, races usually end with more drivers obtaining a classification which is often high. This effect may not be fully captured by the control for drivers finishing and its interaction terms. Finally, a driver's talent has become less important due to technical advances.

How are the Australians performing? According to our estimates, the most talented Australian driver is Mark Webber on position 27, well ahead of the two Australian champions Jack Brabham (47) and Alan Jones (52). But what is more impressive is the aggregate performance of the Australians. There are three Australians among the top half of the 124 drivers who participated in at least 40 races and were thus ranked in *Table 1*. Only Great Britain with 15, France (7), USA (5), Brazil (5), Germany (4) and Finland (4) exhibit more entries among the best 62 drivers. However, even more impressive is the performance of New Zealand. With its three top racers Dennis Hulme (position 25), Chris Amon (33) and Bruce McLaren (40) it is even better performing than Australia. When standardizing country performance according to the size of the population (i.e. the number of drivers among the top 62 divided by population size), it turns out that Finland is first, New Zealand second, Great Britain third, Austria fourth, Belgium fifth, and Australia sixth. But there is another perspective from which the performance of the Australians and the New Zealanders is even more striking. When comparing the number of entries per country among the better 62 racers and the worse 62 racers, respectively, the result is absolutely remarkable: Australia and New Zealand have each three drivers among the better 62, but none among the worse 62 racers. No other country has such a good performance. Belgium exhibits two better and also none worse driver, followed by the USA (5:1), Finland (4:1), Great Britain (15:7) and Brazil (5:3). While Germany exhibits as many better than worse drivers (4:4), the score of many countries is highly negative. Most importantly, France has much less better drivers than worse drivers (7:12), topped only by Italy (3:16) and Japan (0:4). Thus, there is at least some empirical evidence that men from Oceania are the most talented drivers in the world.

V. ROBUSTNESS

We present a number of robustness tests in columns (2) to (5) of *Table 1*. For all these tests the adjusted R2 is between 85 and 90 %. Economists usually only discuss the sign of a coefficient and its significance. They analyze the size and changes in the size of a coefficient less frequently. For this ranking it is essential to analyze the exact size of coefficients in order to compare them with each other. In our case robustness comprises changes in coefficient values and thus changes in the ranking which is a far stricter robustness measure than generally applied.

When searching for the "true" talent of a driver it is, *a priori*, not clear whether we should include any measures concerning attributes of the driver himself, such as experience. Experience is itself a measure which depends on talent as more talented drivers will compete at younger ages in Formula 1. Moreover experience may have an effect on talent.¹³ In the dataset we can capture experience in the form of the number of Formula 1 races a driver participated in. In

¹³ The same applies to the age of a driver itself. Age may have an influence on a driver's performance but the true talent of a driver cannot be separated from his age in reality.

robustness tests we analyze the sensitivity of our statistical assumptions and include the racing experience of a Formula 1 driver in several specifications.

In specification (2) we include two additional control variables which capture the classification of a team partner and a possible home advantage, i.e. if the race is held in the nation where the driver was born. By including the classification of the team partner we control for possible coefficient biases due to self-matching. Self-matching means that teams with good cars search for good drivers and good drivers search for good cars. In the case of self-matching it becomes more difficult to separate the effects of car and driver on the dependent variable, i.e. classification. Although we argue that the separation of cars and drivers is exactly the aim of our estimates, some readers may not be fully convinced. Thus, we include the classification of the team partner as a separate variable to test for robustness. The control variable has a negative sign, its effect is minor and it is statistically insignificant (coefficient = -0.011; standard deviation = 0.007; p-value = 0.126). Consequently, we cannot find evidence for self-matching which is not yet controlled for by our base estimates. The variable for home advantage is negative and significant at the 10-%-level (coefficient = -0.242; standard deviation = 0.134; p-value = 0.071). Drivers are, *ceteris paribus*, faster when driving in their home country. The general ranking changes only slightly when these two additional controls are included. All changes are within single talent coefficient's significance levels. The most important results remain robust to changes in the control variables.

In column (3) we analyze the effects of including experience on the ranking. The experience variable is entered together with the controls for self-matching and home advantage.¹⁴ The experience variable is positive as expected. Inexperienced drivers perform worse than experienced ones. Though the effect is statistically insignificant (coefficient = 0.220; standard deviation = 0.156; p-value = 0.158), and the coefficient size is small compared to the talent coefficients. The ranking itself changes only slightly.¹⁵

We observed almost no changes in the variance of the drivers' coefficients between specifications (2) and (3) when comparing them with specification (1). This is an additional indication that the control variables act as shifting variables for all drivers similar to a constant. As the ranking compared to our preferred specification changes only slightly, the additional control variables affect the measured success of all drivers to the same extent.

In columns (4) and (5) we test changes in the definition of the dropout variable. In these specifications, human dropouts are given the value of the classification of the last arriving driver plus one. Thus, the dropout classification no longer depends on the number of drivers dropping out during a race. We use the same control variables as in specification (2). In regression (5) we also include experience as an additional variable. There are some changes in the general insights. The changes concern drivers whose ranking can hardly be explained by their driving talent. One example of such a driver is the rather unsuccessful Eric Comas.

¹⁴ For drivers of the year 1950 we assume that they are all experienced when starting Formula 1 racing.

¹⁵ We have also tested other types of coding for the experience variable. Especially we tried to look at life cycles by introducing quadratic terms. Results show that the life cycles in Formula 1 racing are rather flat and highly specific to individual drivers. Moreover, drivers seem to drop out of Formula 1 racing quickly as soon as they become less performing. Imposing the same life cycle for all drivers would bias the results for Formula 1 racers which participated in Formula 1 racing for a long time and who have been comparatively successful.

In our preferred specification he ranks 23rd. By changing the definition of dropouts he loses seven ranks but remains surprisingly good.

Looking at *Table A3* confirms the general impression that the proposed ranking in column (1) is very robust to different specification tests. The *table* shows rank correlations as well as correlations between talent coefficients of *Table 1*. The different rankings and the talent coefficients are highly correlated over the specifications estimated.

VI. CRITICAL APPRAISAL OF METHOD AND RESULTS

At first glance the ranking seems intuitive. There are a number of new insights to be gained. However, several critical aspects of the estimations and the results remain to be discussed.

The ranking presented has a certain error probability. But this is not a shortcoming of the ranking. Quite the opposite is the case. All evaluations, rankings and ranking lists suffer from random influences. Talent and capacities of the athletes are often not directly observable. Thus, other rankings hide the high uncertainty and the relative instability by not showing the error probability and the standard deviations of their estimates. In comparison to other rankings which are based on points or wins, our analysis permits us to estimate an error probability and provide estimates of the variance of the talent coefficients. Thus, we do not only explicitly calculate the talent of a driver but also seriously take into account the error probability.

From a technical perspective the high number of dummies might represent a numerical problem of stability and of multicollinearity. Numerical mathematicians (see Schwarz und Köckler, 2004) suggest the calculation of a condition number in order to analyze possible problems of numerical stability. In our case the condition number is 13.111×10^7 . Modern computers work with a precision of 16 floating point operations. Thus, numerical stability is assured. When including additional control variables the coefficients of the drivers change only slightly and they change symmetrically for all drivers.

Over the period from 1950 to 2006, we identified approximately seven changes in cars per driver (including test cars). Over the same time period it is sometimes difficult to compare drivers on the same cars as we analyze cars in their car-year-specific form as mentioned above.

Well-organized teams were not common at the beginning of Formula 1 racing. While two or more drivers used the same car, the racing heroes concentrated on their own success and less on the team's success. Thus, the influence of team orders was probably negligible. Today, the team's success is important too and weaker drivers in a team sometimes make room for their team partners. Unfortunately, we cannot control our estimates for such team orders.

Sometimes people state that a driver's contribution to success depends not only on his own driving talent but also on his talent to improve the team's car. Thus, it is often said that Michael Schumacher had exceptional abilities not only with respect to driving quickly but also to making the car going fast. In our regressions we only control separately for a driver's capability and a car's capability and it is not possible to estimate the influence of a driver on his car. Drivers and cars are treated as dummy variables in the estimates. However, the commonly expressed opinion is not necessarily true. The relationship might also go in the other direction, i.e. cars are adapted to the specific driving style of the team's number one driver. It is plausible that Michael Schumacher benefited heavily from this effect.

VII. CONCLUDING REMARKS

Formula 1 drivers are faster the more talented they are and the higher the quality of their car. This paper is the first to try to evaluate the true talent of a Formula 1 driver by separating it from the performance of his car. Most rankings today represent a simple sum of achieved points and do not reflect a driver's true talent. We treat talent as independent of the cars used and a number of other characteristics. People often forget that wins, podium positions or points represent random variables which are influenced by a driver's talent as well as a number of other factors.

The results of this ranking distinguish themselves from other published rankings. Clearly, a certain number of wins is necessary to be among the best. However, podium positions are not a sufficient indication of driver talent.

By using linear regressions and controlling for driver and car dummies we can separate the talent of Formula 1 stars from what their car contributes to success. Michael Schumacher has had the most absolute wins and is among the TOP-10 drivers. However, he is not the top ranked driver. The best Formula 1 driver ever is Juan Manuel Fangio.

Our analysis shows that Formula 1 data are not only of interest when trying to evaluate a driver's talent or in order to establish a world ranking. Additional economic and non-economic applications can be envisioned. By analyzing changes in the rules of Formula 1 driving we could quantify incentive effects. The analysis of dropouts also provides interesting insights on risk-taking. Other interesting questions are less of economic importance but of interest in general discussions. They represent questions of the typical "What if?" form, for example, "What if Senna did not have his accident". Additionally, we could think of calculating life cycles for drivers as well as evaluating teams and cars.

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APPENDIX

Table A1: Descriptive Statistics

Variable	<i>N</i>	<i>Min</i>	<i>Max</i>	<i>Mean</i>	<i>Standard Dev</i>	<i>Median</i>
GRANDPRIXDIST	768	52.920	804.670	328.182	78.008	307.516
CIRCUMFERENCE	768	3'145.000	25'579.000	5'647.805	3'552.131	4'627.000
ROUNDSGP	768	12.000	200.000	66.743	23.209	68.000
WEATHER	768	-2.000	2.000	1.189	1.217	2.000
AGEDRIVERSTART	302	19.000	54.000	28.844	6.180	28.000
AGEDRIVEREND	302	20.000	56.000	34.328	6.423	34.000
DRIVERSINRACE	302	1.000	256.000	51.831	55.785	31.000
DRIVERSWINS	302	0.000	91.000	2.543	7.890	0.000
DRIVERSPODIUMS	302	0.000	154.000	7.626	16.447	1.000
DRIVERSCARS	302	1.000	25.000	6.818	5.040	6.000

Source: own calculations based on FORIX Data from 1950 to 2006.

Table A2: Identification of Dropout Periods

Year	Average of relative dropouts	Standard deviation	Observations (races)	<i>z</i> -value
1950	0.487	0.125	84	4.273
1960	0.396	0.123	57	6.685
1966	0.557	0.116	43	5.183
1970	0.453	0.110	129	5.656
1979	0.525	0.109	171	6.298
1990	0.449	0.121	196	8.164
2002	0.312	0.134	88	

Source: own calculations based on FORIX Data from 1950 to 2006. The *z*-value serves to test the expected value of average relative dropouts (approximate procedure).

Table A3: Correlation between Specifications

	Rankings of (1)	Rankings of (2)	Rankings of (3)	Rankings of (4)	Rankings of (5)
COEFFICIENTS OF (1)		0.999	0.996	0.961	0.952
COEFFICIENTS OF (2)	0.999		0.996	0.960	0.951
COEFFICIENTS OF (3)	0.998	0.998		0.966	0.961
COEFFICIENTS OF (4)	0.975	0.974	0.975		0.997
COEFFICIENTS OF (5)	0.972	0.971	0.974	0.999	

Source: own calculations based on FORIX Data from 1950 to 2006. The correlations to the upper right represent Spearman correlations of the ranks of specifications (1) to (5) of Table 1. The correlations to the lower left represent Pearson correlations of the specifications (1) to (5) of Table 1.