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## Race to the Podium: Separating and Conjoining the Car and Driver in F1 Racing

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### Abstract:

This paper provides a statistical estimate of the breakdown in race outcomes in Formula One races between the two most important inputs: driver skill and car technology. Financial data and racing results from the 2012-19 F1 seasons are used to estimate a combined driver and team censored regression model for each season. Treating each season uniquely allows for the exclusion of weather and track specific variables common to other statistical studies of F1 racing. Our use of financial data provides an answer to the economic question of how should F1 teams allocate their scarce financial resources. The so-called “80-20” rule distinguishing team effects and driver effects is found to be a very rough approximation to the output shares for teams and drivers. A strong complementarity exists between driver skill and car technology that distorts the rule. The return to driver salaries and team budgets are both positive in term of race outcomes, but at diminishing rates.

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## INTRODUCTION

Formula 1 motor racing is perhaps the best example of a sport that relies on a critical interaction between human and machine to produce a winning outcome. The Formula 1 circuit began in 1950 with a series of six races to determine an overall champion in circuit track racing<sup>1</sup> in the world. In the early days of Formula 1 (F1), race cars were crude and unsafe. The driver relied on a steering wheel, accelerator and brake pedal, stick shift and clutch pedal, but mostly on his skill and bravery. Crashes and car breakdowns were frequent. Race teams were very fluid during a season and from season to season. Teams would experiment with different models of cars and different drivers during the race season. There was very little consistency or technology in F1 racing. Over the decades since, the technology and safety of F1 cars has greatly improved, as have the race tracks that host races in the F1 circuit. Race times have decreased in concert with increases in average speeds due to better driver fitness and training, better driver compensation, and safer race cars that encourage pushing the limits of the car's capabilities.<sup>2</sup> However, the most notable and visible changes since the early days of F1 are the advances in driving technology. These include technological innovations in the cars themselves, as well as greater skill and efficiencies in pit crews and team management.

While the F1 drivers of today are highly skilled and trained, one could surmise that the technological advances of the cars and teams play a much larger role in race outcomes than they did decades ago.<sup>3</sup> Off the track the race is composed of the teams spending large amounts of

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<sup>1</sup> As opposed to oval track racing, such as the NASCAR circuit in the United States.

<sup>2</sup> The number of fatalities in F1 peaked at four in the 1958 season and then experienced a gradual decrease. The last crash resulting in a fatality occurred in the 2014 season.

<sup>3</sup> Barzel (1972) found that technology advances played a critical role in the faster average speeds attained in the Indianapolis 500 motor race from 1911-1969. Mantel et al. (1995) estimate a smooth progress function based on time trial speeds at the Indianapolis 500, suggesting that technology progress does not occur in discrete jumps.

resources to develop the new technologies to beat their competitors on the track. Many of these new technologies are now commonplace in production passenger cars: antilock brakes, traction control systems, multi-clutch transmissions, paddle shifters, lightweight body shells, energy recovery systems, and so on. Unfortunately for the F1 teams that develop these new technologies, their racing advantages are quickly dissipated as teams learn to adopt technologies developed by other teams. Nevertheless, the free-riders do not appear to discourage the wealthier teams from investing large amounts in the hopes of gaining a competitive edge.

Our task in this paper is to describe an answer to the question of which component of the F1 team contributes more to racing success, the driver or the team which we identify with technology.<sup>4</sup> Separating the contribution of each is made difficult due to the complex interaction between driver and car. The so-called “80-20 rule” was suggested by 2016 F1 champion Nico Rosberg – that the team and car account for 80% of the winning success, with driver skill accounting for only 20% (Boll (2020)). We employ a regression method that estimates the proportion of variation in racing outcomes that is “explained” uniquely by the specific driver, and uniquely by the specific team that employs the driver. We also identify the proportion of variation that is due to the interaction between the driver and his team, and we control for drivers that retire from the race due to accidents or mechanical faults. Our results suggest that the 80-20 rule slightly overestimates the driver contribution, while the team contribution alone is greatly overestimated. The interaction, or synergy, between driver and team accounts for up to 40% of the variation in driving outcomes, suggesting a significant degree of complementarity between team quality and driver quality. However, a significant unexplained (and possibly random)

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<sup>4</sup> We do not try to specify all elements of the team that are important since our measures are confined to aggregate team expenditures and driver expenditures.

portion remains that could be determined by factors specific to events happening on the track each race day that are unpredictable (excluding weather and track conditions).

### THE FINANCES OF FORMULA 1

The F1 race circuit and its rules have become much more standardized over the decades since 1950. Although new race-tracks are occasionally added and some are removed from the circuit, a F1 season is now typically composed of about 20 races<sup>5</sup>. Also typically, 10 race teams each race two cars in each race. Each team hires two drivers, although backup drivers are held on standby in the event the senior drivers cannot race. Race teams spend a great deal of money to launch a race team and compensate their drivers. A team must spend well over \$100 million per season just to be on the circuit and spend much more to find drivers who finish consistently on the podium (the top three places). Race teams that are housed in the U.K. are required to make their financial statements public, however teams housed in the rest of Europe face much more relaxed reporting rules.<sup>6</sup> Similarly, driver compensation is not made publicly available. Table 1 below provides estimates of team expenses and driver compensation for the 2019 F1 season.

<Table 1 inserted here>

Drivers and teams earn points for finishes in the top ten positions on a rapidly declining scale.<sup>7</sup> The highest point finishers at the end of the racing season are declared the driver world

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<sup>5</sup> The first F1 season in 1950 featured only 7 races, increasing to 16 races by the 1984 season. The 2020 season featured 21 races.

<sup>6</sup> Race teams housed in some countries, such as Switzerland, are not required to make public their financial statements, while some teams combine their racing budgets into their retail car operations (Ferrari, Mercedes) making it difficult to gain any detail.

<sup>7</sup> First place finishers earn 25 points, while the 10<sup>th</sup> place finisher earns just one point. The bottom ten finishers earn no points. In the early years of F1, points were allocated in different ways.

champion and the team world champion. F1 racing is a lucrative business enterprise. In 2016, total revenues from all sources were approximately \$28 billion with a net profit of approximately \$1.8 billion.<sup>8</sup> Each team receives an equal share of a portion of total revenues from the F1 season, plus bonus money based on their final point positions at the end of the racing season (denoted as the Constructor's Championship). The total bonus payouts to all ten racing teams (including the equal shares) at the end of the 2016 season totaled approximately \$1.05 billion, with the largest payout, \$209 million, going to Team Ferrari, and the tenth-place finishing Caterham team receiving \$59.8 million. Residual profits accrue to the Formula One Group, an investment company that organizes F1 races and hold the rights to its properties.

Although F1 is profitable, the magnitude of team expenses and driver salaries result in only modest profits or losses for most teams. Those teams that are a subsidiary of a larger parent company (Ferrari, Mercedes, McLaren, Alfa Romeo, Renault, Aston Martin (Red Bull)) can rely on cross-subsidies to offset losses since their parent companies benefit from the technologies developed for their retail cars and the promotion of their corporate brand. Smaller teams that operate independently (Williams, Racing Point, Haas, etc.) experience far greater turnover from season to season due to the uncertainty of profitability.

The technologies contained in a modern F1 race car are expensive. The standard 1.6 liter turbocharged engine (power unit in F1 terminology) that must be rebuilt after each race costs approximately \$10.5 million. The steering wheel, with its computerized components that control many functions of the car, is a much more affordable \$50,000. Table 2 below provides a breakdown of the component costs of a typical F1 car.

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<sup>8</sup> <https://www.totalsportek.com/f1/formula-one-prize-money/>

<Table 2 inserted here>

Driver compensation is considerable, but its distribution is highly skewed, as evidenced in Table 1. This is not unusual for sports that are rank-order tournaments in which a “players” output is difficult to measure. Prizes that increase exponentially with rank finish will entice the greatest effort from the drivers, particularly drivers at the low end of the pay scale.<sup>9</sup> This ensures healthy competition between the drivers and races that become too predictable. Unfortunately, the skewed distribution of driver compensation has not prevented the outcomes of F1 races to become quite predictable, despite attempts by the FIA to maintain parity through frequent rule changes. This issue falls under the much larger issue of competitive balance in the sports economics literature. Oddly, we were able to find only a single paper that measured competitive balance in F1 (Judde, Booth and Brooks, 2013) and only for seasons prior to 2010. Table 3 presents the Gini coefficients and their standard errors for the driver points championship for the 2010-19 seasons. The high Gini coefficients for each season suggest that there is very little parity in the driver point totals, with the top few drivers earning the bulk of the points.

<Table 3 inserted here>

More recently, teams that spend more earn more championship points. The coefficient of correlation between team expenses (not including driver compensation) and final points in the Constructor’s Championship is 0.828 and 0.771 for the 2018 and 2019 seasons respectively. Moreover, the Gini coefficients for final Constructor’s points at the end of each season in Table 4 are remarkably consistent since the 2010 season. This despite the changing budgets of each team each season and the turnover of teams from season to season. There is a strong consistency

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<sup>9</sup> There are numerous references. See Lazear and Rosen (1981) or Nalebuff and Stiglitz (1983) to name two.

year over year as no Gini in a year is outside a band of two standard errors of any year's value for either drivers or teams. Further, there is much more parity among the teams than among the drivers.

<Table 4 inserted here>

### THE SKILLS OF F1 DRIVERS

Drivers who have the skills to move up to F1 racing from the junior circuits (F3 and F2) arguably drive the most technologically advanced cars in the world. These are difficult machines to drive well and better results should come with experience. Significant changes in the final driver points from year to year are largely due to drivers moving to new racing teams. Typically, the top three or four positions show remarkable stability over a number of consecutive seasons, with most of the movement at the lesser point positions. The wealthy teams often feature a senior team with the top two drivers in their driver system, followed by a lesser team with the younger up and coming two drivers. The senior team could also be driving the more proven car, while the lesser team drives a car that could still be under development and not perform as well, though this is not always the case. Sauber has been the development team for Ferrari off and on for decades, while more recently, Toro Rosso has performed the same function for Red Bull, and Williams for Mercedes. Changes in team sponsorship can result in changes in team names, so tracking the swings in driver final point positions from season to season can be tricky. Table 5 presents a list of notable changes in final driver points standing since the 1990 F1 season.

<Table 5 inserted here>



Large swings in final driver point positions are almost always the result of drivers moving to different teams – very rarely the result of a team moving up or down the standings with the same driver. The most notable are the cases where a driver wins the F1 driver title having struggled with a lesser team in the previous season. These include Kiki Rosberg in 1982, Nelson Piquet in 1987 and Jensen Button in 2009. Although Niki Lauda won the title in 1984 with McLaren, he drove for McLaren in the disastrous 1983 season in which he dropped out of 11 of 15 races with mechanical failures. The car was greatly improved for his winning 1984 season, finishing the race in 9 of 15 attempts and never placing lower than second on the podium. Drivers that are promoted from the development team to the senior team typically benefit from a better car and more extensive team support system. Examples include Felipe Massa in 2006, Daniel Riccardo in 2014 and Charles Leclerc in 2018. Although the drivers might improve their driving skills in one season, it is most likely that the move to a better car and team accounts for most of their move up the points standings. In a few instances, a significant improvement in financial backing allows the team to develop a better car and provide more team support to the same driver. This was the case for Elio de Angelis in 1984 when Lotus received a significant cash injection from investors, resulting in de Angelis moving from 18<sup>th</sup> to third in one season. A few drivers choose to move to new teams after achieving success in F1 with disastrous results. Damon Hill won the points championship in the 1996 season with Williams and moved to the new Arrows team for the 1997 season, finishing a distant 12<sup>th</sup>. This is most surely due to the lesser ability of the Arrows car and less team support and not due to a deterioration in Hill's driving skills.

The driving skills of F1 drivers can take a considerable amount of practice to acquire. Only those drivers who demonstrate superior skills through race victories advance to the higher levels

of racing circuits, culminating for only a few on an F1 team. Skills are developed at an early age, typically in the early teen years through cart racing, moving on to cars that are much smaller and less powerful than F1 cars in a succession of junior racing circuits, rising to Formula 3 to Formula 2 to F1 by their early twenties. The larger F1 teams (with greater financial resources) identify potential drivers early in their junior careers and sign them to contracts to compete in their unique racing programs (Red Bull, Ferrari, Mercedes, McLaren). Upon graduation to F1, these contracted drivers compete with the development F1 team with the hope of eventually moving up to the senior team. For many drivers, promotion to the senior team never happens and the drivers are left to join other lesser F1 teams. This guarantees a constant supply of skilled drivers for the larger, wealthier F1 teams, while generating positive externalities for the lesser teams in the form of competent drivers without having to spend resources on their own driver development programs.

In normal circumstances, drivers who are new to F1 are not expected to win championships or place on the podium. There are only a few examples of those who do after being placed on a senior team from the start of their F1 careers. Jacques Villeneuve began his racing career in F1 in 1996 for Ferrari and finished second in the overall points standings, then won the points championship in 1997 with Ferrari. Villeneuve left Ferrari to join the Williams team for the 1998 season, finishing fifth in the final standings. Villeneuve retired from F1 in 2006, after racing with the BAR, Renault and Sauber teams, never coming close to achieving his early results with Ferrari. Lewis Hamilton spent his first season in F1 (2007) with the senior McLaren team and finished second in the overall points standings, then winning the point championship in his second season. His driving talent was obvious from the start of his F1 career, hence Hamilton

never toiled with lesser teams. Instead, he moved to Mercedes for the 2013 season and won consecutive driving titles from 2014 through 2020.

The casual evidence suggests that drivers enter F1 with similar skill sets and driving abilities, but those who move to teams with superior cars and team support or are lucky enough to begin their F1 careers with these teams, achieve superior results and possibly world championships. This leads one to question the importance of driving skill, versus having a superior car and team support, in determining podium results. The much higher wages paid to the top drivers suggests that the racing teams value their driving skills according to racing success, however the top teams have a much greater ability to pay higher wages. In the next section of the paper, we develop an econometric method to attempt to disentangle the contributions of driver skill and car technology in determining the order of finish. Our purpose is not to suggest which drivers were the best (Eichenberger and Stadelmann (2009), Phillips (2014), Bell *et al* (2016)), or to determine if F1 seasons achieve competitive balance among the racing teams (Jude, Booth and Brooks (2013)). We believe it is quite logical that driving skill, car and team technology, and the interaction between the two contribute in their separate ways to race outcomes. However, we make no attempt to judge whether drivers are under or overpaid or whether F1 rules regarding car technologies and team support are fair.

We believe that our approach offers a number of useful innovations. By focusing on single F1 seasons, we can ignore the effects of track specifics and weather since these will only affect the distribution of rank finishes but not their average value. We also incorporate financial variables, namely team budgets and driver salaries, that have not been used in previous studies (Eichenberger and Stadelmann (2009), Phillips (2014), Bell *et al* (2016)). This allows us to estimate the most effective uses for scarce finances in achieving winning results. Finally, we

estimate the proportion of variation in rank finishes attributable uniquely to driver skill, team quality, the interaction of driver and team, and randomness.

### ECONOMETRIC MODEL

The total variation in the rank finishes of each race in each season is composed of the unique variation due to (i) the skill of the driver, (ii) the unique variation due to the quality of the car and team, (iii) the variation shared by the driver and the team, and (iv) the unexplained variation due to random factors. Our first task is to estimate each of these components. Second, we combine the variables in a single regression model to gauge their impact on the rank finish of each race. We chose to use the rank finish of each driver as the measure of performance, however other measures are possible. The average lap time in each race is available, but it is not always indicative of the order of finish, nor is the fastest lap time. The measured distance behind the winner of each race is only available for drivers that finish within one lap of the winner. It is also greatly influenced by the situation in each race as the race progresses. If the distances are close near the end of the race, those drivers behind the leader could push their cars harder to try to overtake and improve their rank finish. This might not be the case if the distances are far apart – in that case, the incentive is just to maintain the finishing rank position. The rank finish is an ordinal measure that does not necessarily reflect the average lap time or the measured distance from the winner, but it is easily available and is the ultimate measure of importance for the team and the driver since points are awarded based only on the rank order of finish. Phillips (2014) uses points from each race for his analysis, but points have been assigned using different criteria in

some years and many drivers earn no points in a race which limits the decomposition of team versus driver effects which is important for our analysis. Bell *et al.* (2016) also assign points according to their own scale.

It is difficult to select variables that capture the quality of the car and team, and the skill of the driver. The rules regarding technical features of the cars and how the teams operate, both in the pits, the garage, and in the boardroom, are very strict and mandated by the FIA. Thus, there is a great deal of homogeneity, with the exception of team finances (although forthcoming rule changes will reduce the allowed expenditures of the larger teams significantly). The large high spending teams spend considerable resources in developing new technologies that stay within the rules, but yet can give a significant edge in car performance.<sup>10</sup> Marino et al. (2015) constructed an ordinal measure of the technological component of each car by consulting a panel of industry experts. Teams were assigned a value between 0 and 3 based on their innovation responses to FIA rule changes for the 1981-2010 racing seasons. The purpose of the study was to estimate if FIA rule changes restricting car technologies incentivized or discouraged innovation, with the latter found to be true due to difficulty of the necessary knowledge acquisition. F1 teams are very secretive in revealing performance data, such as power unit horsepower, wind tunnel results and so on. Unfortunately, there is no broadly available measure of car technology beyond the rank finish of each race and the points standings at the end of each season.

Estimates of team expenditures (excluding driver salaries) have become available for recent racing seasons and we include the natural log of team expenditures (*Inteamexp*) excluding

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<sup>10</sup>A recent example is the Dual Axis Steering (DAS) system developed by Mercedes for the 2020 F1 season. The DAS system allows the driver to change the front wheel alignment of the car, resulting in a significant improvement in cornering. After an appeal by other teams, the FIA allowed the DAS system to be used, however it has since been banned.

driver salaries as an explanatory variable.<sup>11</sup> We compiled these estimates from a variety of sources listed in the appendix.<sup>12</sup> We chose the deviation of the average pit stop time for each team from the average pit stop time (*devpittime*) in each race as a measure of team quality (the average pit stop time differs for each race due to the overall length of the pit lane)<sup>13</sup>. The starting grid for each race is determined the day before the race based on the fastest lap time in three qualifying sessions. A better position in the starting grid (poll position) gives each team a better chance of a podium finish. We included the poll position of each driver (*poll*) in each race. We also included a dummy variable (*teamdnf*) taking on the value one if the car did not finish the race due to a mechanical fault (and not a driver error).

Track characteristics may also affect the performance of each team's cars. Tracks vary significantly in their length and number of turns, and somewhat in the number of DRS zones<sup>14</sup>. However, the unique structure to the racing season in F1 made the inclusion of variables measuring track characteristics unnecessary. All drivers face the same track characteristics in each race. If no cars drop out of a particular race, the average rank finish is simply equal to half of the number of cars racing. A change in track length, number of turns, number of DRS zones, or any other fixed track characteristic will have no effect on the average rank finish with the same number of cars racing in each race. The marginal effect of a track characteristic is

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<sup>11</sup> Recent 2021 rule changes limit overall team spending to \$145 million but exclude driver salaries and several other expenditures (Bol, 2021), so it remains to be seen if it will change the impact of team spending on outcomes.

<sup>12</sup> Data sources for all variables are listed in the appendix.

<sup>13</sup> A measure of pit time excluding the run in and run out times would also be an interesting measure of team efficiency, but during the period we study only the total pit times were recorded.

<sup>14</sup> In specific portions of each track, cars pass through a Drag Recovery System (DRS) zone that allows the rear wing of the car to open, reducing the aerodynamic drag of the wing and increasing the speed of the car. The wing is closed when the car leaves the DRS zone. The system is enabled when a car is less than one second behind the car in front.

essentially the number of cars that drop out of the race.<sup>15</sup> Equation 1 describes the regression relating team performance to rank finish.

$$rankfinish_{i,j,n} = \alpha_0 + \alpha_1 ln_{teamexp}_i + \alpha_2 dev_{pittime}_{i,n} + \alpha_3 teamdnf_{i,j,n} + \alpha poll_{i,j,n} + e_{i,j,n} \quad (1)$$

The structure of the team regression dataset is important. Each team has two cars in each race over a number of races in each season. The subscript  $i$  denotes the team, the subscript  $j$  denotes the driver on team  $i$  ( $j = 1, 2$ ), and the subscript  $n$  denotes the race during the racing season. Note that the  $ln_{teamexp}$  variable does not vary by team or race and thus serves as fixed effects, negating the need for a fixed effect variable for each team.<sup>16</sup>

All drivers who race in F1 are highly skilled and the differences in skills can be very slight between a champion and a contender. We could not easily obtain skill data specific to each driver that could be treated as an input into a hypothetical production function. Outputs of each driver are easily obtainable, such as podium finishes, championships, season points, etc., however these are outcomes, not inputs. Our driver regression model in (2) is rather simplistic

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<sup>15</sup> For instance, if the estimate of the marginal effect of a track with one more turn is equal to -0.5, it would suggest that the average rank finish decreases by half a position. This can only occur if one car drops out of the race due to a driving or mechanical fault. Since the independent variable  $teamdnf$  already accounts for teams with non-finishing cars, track characteristics should have no marginal effect on the average rank finish.

<sup>16</sup> Since the team expenditures are the annual totals, they do not change for each race. Using the within estimator (Hill et al (2017), p. 642) to account for fixed team effects subtracts the mean annual expenditure for each team from its total annual expenditure, resulting in a column of zeroes for the team expenditure variable and a slope coefficient cannot be estimated. Using dummy variables for fixed effects results in the same issue. We chose to include the team expenditure variable and exclude fixed effects variables for each team on the basis that total team expenditures captures the majority of variation accounted for by unknown heterogeneous variables that could bias the slope coefficients.

but allows for an estimate of the variation in rank finishes due to the driver, whether it be the driver's skill or some other intangible factor specific to the driver. We included the natural log of the annual salary (*lnsalary*) paid to each driver as a measure of the driver's historical marginal product. Experience could be an important factor to a driver's performance if it is associated with the accumulation of greater racing skill and track knowledge. The number of career F1 race starts prior to the particular race (*racestarts*) and its squared value (to capture any non-linearity in the career profile) were included as explanatory variables. Cars that do not finish a race due to a driver fault (typically a crash) were captured by a dummy variable (*driverdnf*). Drivers were not distinguished by team in the driver regression model.

$$rankfinish_{i,n} = \beta_0 + \beta_1 lnsalary_i + \beta_2 racestarts_{i,n} + \beta_3 racestarts_{i,n}^2 + \beta_4 driverdnf_{i,n} + \beta_5 poll_{i,n} + u_{i,n} \quad (2)$$

As already mentioned, the variables *Inteamexp* and *lnsalary* loosely act as fixed effects variables in the team and driver regression models respectively since they do not vary from race to race. We assume that an unobservable latent variable exists that measures the performance of the driver and car. One thought was to use the elapsed time from start to finish for each car in each race since these data are available for the sample period. A superior driver in a better-quality car should achieve a faster elapsed time<sup>17</sup>, however times are complicated by race

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<sup>17</sup> Elapsed times are measured from when each car crosses the start line to crossing the finish line in the last lap. In some cases, the car with the shortest elapsed time does not win the race if it started the race with a poor poll position.



strategies and yellow flags.<sup>18</sup> The rank position at the end of the race is an imperfect measure of performance since the values for the variable *rankfinish* are bounded by one and the number of drivers taking part in the race (between 20 and 24 in our sample period).

A least squares regression using *rankfinish* as the dependent variable can result in predicted values that fall below one or above the total number of cars in the race. We employ a censored regression model that combines (1) and (2) with the assumption of normally distributed errors. The computation of the marginal effect of each independent variable on the latent variable is a function of the estimated slope coefficient and the cumulative probability at a specific value of the independent variable (Hill, Griffiths and Lim (2017), p. 720), typically the mean value.

The first task is to decompose the total variation in the rank finish for each driver into the variation explained by the driver skill and the variation explained by the team quality. The procedure is to:

1. Compute the total variation in the *rankfinish* variable across the  $K$  teams and  $N$  races in a single season,  $SST = \sum_{i=1}^K \sum_{n=1}^N (Y_{i,n} - \bar{Y})^2$ .
2. Estimate the team regression model in (2), compute the  $R^2$  and compute the residuals.
3. Use the residuals from step 2 as dependent variable in the regression of the driver model in (1) and compute the explained variation,  $SSR = \sum_{i=1}^K \sum_{j=1}^2 \sum_{n=1}^N (\hat{e}_{i,j,n} - \bar{e})^2$ .

The percentage of variation in *rankfinish* attributable to the driver alone is

$$R_D^2 = SSR/SST \text{ (SST computed from step 1).}^{19}$$

<sup>18</sup> A yellow flag instructs the drivers that an accident has occurred on the track. Drivers are required to slow to a maximum allowable speed until the yellow flag is removed. The result is that cars lose their time advantage over lesser cars as cars bunch together.

<sup>19</sup> Of course, one could use the driver regression model in (1) as the estimated model in this step 2 and then regress the residuals from that model on the team regression model in (2). The decomposition of the variation in rank finishes is identical using either method.

4. Compute the  $R^2$  in the driver regression using *rankfinish* as the dependent variable.

The difference  $R_{TD}^2 = R^2 - R_D^2$  is the variation shared by the driver, the team and *rankfinish*.

5. The total variation attributable uniquely to the team is computed as  $R_T^2 =$

$R^2(\text{step 1}) - R_{TD}^2$ .

6. The unexplained variation in *rankfinish* is computed as  $1 - R_T^2 - R_{TD}^2 - R_D^2$ .

The second task is to estimate a combined regression model of (1) and (2) to explain the rank finishes in each race in each season, with an additional independent variable that is the interaction between the driver salary and the team budget ( $\ln S * \ln B$ ) since the effect of an increase in the driver salary is dependent upon the size of the team budget, and vice-versa. Teams with larger budgets tend to hire better drivers that come with higher salaries, while smaller teams hire cheaper drivers who may be less experienced or past their best skill levels. To see the impact of each of the variables on the rank finish, we combine the variables from both the team and driver model and estimate their effects as equation 3:

$$\begin{aligned} \text{rankfinish}_{i,j,n} = & \gamma_0 + \gamma_1 \ln \text{teamexp}_i + \gamma_2 \text{devpittime}_{i,n} + \gamma_3 \text{teamdnf}_{i,j,n} + \\ & \gamma_4 \text{poll}_{i,j,n} + \gamma_5 \ln \text{salary}_i + \gamma_6 \text{racestarts}_{i,n} + \gamma_7 \text{racestarts}_{i,n}^2 + \gamma_8 \text{driverdnf}_{i,n} \\ & + \gamma_9 \text{poll}_{i,n} + \gamma_{10} \ln B_i * \ln S_i + v_{i,j,n} \end{aligned} \quad (3)$$

## RESULTS

### The Decomposition of Total Variation

The four-step procedure outlined in task one above was performed for each F1 season individually. We thought it best to not “stack” the F1 seasons to create a panel dataset since the turnover of teams and drivers from season to season. The number of races and the tracks used also differed somewhat over the sample period, resulting in an unbalanced panel with some drivers and teams having very few observations.

The steps outlined in the previous section provide the estimated percentage of total variation in the rank finish due to the team alone, due to the interaction of the driver and team, and the unexplained variation. Table 6 reports these estimates for the 2012-19 F1 seasons based on the censored regression results for the team and driver regression models.<sup>20</sup> The results suggest that the skill of the drivers contributes the least to explaining the rank finishes, ranging from 9.88% in 2015 to 20.07% in 2017. In all F1 seasons, the team contribution accounts for a larger share of the variation in rank finishes, ranging from 14.85% in 2013 to 28.49% in 2018. Averaging across the 2012-19 F1 seasons gives values of 13.73% and 20.66% for drivers and teams respectively. The interaction of driver and team accounts for the largest share of the variation in rank finishes in each season, ranging from 28.41% in 2012 to 47.55% in 2013, and averaging 33.75% over all eight seasons. The intuition of this shared variation is similar to an interaction term in a regression model. The performance of a team is enhanced by a better-quality driver and vice-versa. The largest effect occurs when a top driver is placed on a top team and the smallest effect occurs when a lesser driver is placed on a lesser team. Generally, the teams with the largest budgets also hire the highest paid drivers (Mercedes, Ferrari and Red Bull in particular). The unexplained variation in rank finish account for between 22.14% (2018) and

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<sup>20</sup> The percentages reported in Table 6 are not sensitive to whether the censored or least squares regression estimates are used for the computations.

34.99% (2012). These are random factors, outside of retirements due to crashes and mechanical issues, that affect the final order of finish.<sup>21</sup>

<Table 6 inserted here>

### The Marginal Effects of the Explanatory Variables on Rank Finish

The censored regression coefficient estimates and the marginal effects of the combined regression model (3) for the 2012-19 F1 seasons appear in Tables 7-10. We include the least squares (OLS) estimates for comparison. The standard errors are computed using the Huber-White heteroscedasticity consistent computation. The measure of fit for the combined regressions using the marginal effects is not well defined, so it is not reported and is not critical to the results to follow.<sup>22</sup>

Most of the estimated coefficients are statistically significant at 95% confidence in the 2012-19 censored team regression models, with the exception of the pit time deviations that were significant in only the 2015 and 2012 seasons. The effect on the rank finish of a \$1 million increase in the average team budget is given by  $\frac{\hat{\gamma}_1}{teamexp}$ . Clearly moving up to the winner's podium in F1 comes at a considerable increase in the team budget, but the cost varies from season to season. For example, a team that consistently finishes fifth in the rank finish in each

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<sup>21</sup> A word of warning is appropriate here. We are not estimating a production function for F1 racing. Although we discuss complementarity of inputs, the data at hand are not adequate to provide a standard functional characterization since generally only two drivers characterize a team each season. Consequently, writing output as a function of both team and driver leads to collinearity as the driver is the team. More subtle characterization of the inputs is needed to develop a true production function.

<sup>22</sup> This is because in the censored regression the latent variable for performance is not observable, so a sum of squared deviations for the latent variable cannot be computed. However, the rank finish for each driver and car is observable, so its sum of squared deviations can be computed and consequently an  $R^2$ .

race needs to increase its team budget by an estimated \$104.03 million  $[( -2 / \frac{-3.802}{197.76} ) * \$1 \text{ million}]$  to finish in third place consistently in the 2018 season, while costing \$84.78 million  $[( -2 / \frac{-3.457}{146.54} ) * \$1 \text{ million}]$  in the 2012 season.<sup>23</sup> The necessary spending varies each season, largely due to differences in the average team budgets. The deviation in the team average pit time from the average across all teams results in a considerable improvement in placing in only the 2015 season, although achieving even a one second decrease relative to the average is a large amount in the recent era of F1. Reducing the average pit time by  $1/0.377 = 2.653$  seconds, relative to the average of all teams, returns a one position improvement in the rank finish in 2015, but has no statistically significant effect on rank finish in the other seasons. However, this must be done without increasing the team budget. Not finishing the race due to mechanical issues with the car results in an average increase in the rank finish of between seven and ten positions, depending upon the season.

The importance of a good poll position to a race result is clearly demonstrated in the combined regression results. For the cars that finish the grand prix race, a one position improvement in the poll position results in a predicted improvement in the rank finish of between 0.276 and 0.456 positions over the 2012-19 seasons. Establishing a poll position relies heavily on the speed and handling of the car, as well as the ability of the driver to negotiate corners and straight sections efficiently. Teams need to focus on these factors when determining and spending their budgets.

<Tables 7-10 inserted here>

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<sup>23</sup> We have not adjusted for inflation.

Evaluated at the average driver \$8.56 million salary for the 2019 season, a \$1 million increase in the driver's salary<sup>24</sup> results in an improvement in the rank finish equal to  $\frac{1.189}{8.56} = 0.139$  positions, hence a driver must be paid an additional \$7.19 million to improve by one position, holding the other independent variables constant. This increase in salary is strongly associated with driver quality and race experience. Greater race experience does not improve the average standing at the end of the race, with the exception of the 2016-18 seasons in which greater race experience had a favorable significant effect, albeit with diminishing returns. We believe this could be a statistical artifact due to a small number of drivers with considerable years of racing experience who drove for the less competitive teams in most of the seasons in the sample. A driver who did not finish a race due to a driving error (crash) averaged between a 8.43 and 11.33 worsening in rank finish, slightly higher than the team DNF value.

#### RULE CHANGES AND COMPLEMENTARITIES

The 2012-19 seasons contained several seasons that marked significant rule changes to how the cars are constructed and their technical limits. Rule changes are typically determined by the FIA to promote greater parity in team budgets and the availability of technologies, as well as to increase driver and fan safety. Rule changes enacted in the 2012 season were designed to improve parity on the track and make driving safer. These changes required drivers to quickly adapt to new race strategies (passing rules, yellow flags, cornering lines, etc.), however only modest technical changes were made to the cars. Rule changes for the 2014 season also reflected the FIA's concern for environmental responsibility by requiring all cars to use turbo-hybrid

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<sup>24</sup> Although we speak in terms of an increase in salary, we interpret it to reflect the driver's expected marginal product.

engines (power units) that utilized two electric motors in addition to their smaller 1.6 liter V-6 gasoline engines.<sup>25</sup> The result was a far more fuel-efficient power unit that produced fewer exhaust emissions. Other changes for 2014 included the elimination of some performance-enhancing air effects to make the cars safer (lowering the front nose, eliminating side diffusers, etc.). Smaller teams struggled with the move to these expensive technologies and took several seasons to competitively adapt.

Table 6 reveals that the variation in rank finishes explained by driver skill reached 16.7% in the 2012 F1 season, perhaps reflecting the rule changes that emphasized greater driving skill and strategy on the track. The interaction plus team shares of the variation totaled 48.31%, the lowest value for the 2012-19 sample period. The significant rule changes to the cars in the 2014 season corresponded with a decrease in the driver share of the total variation to just 11.52%, while the team share increased to 22.62%. These percentages are significantly different from their 2012 values based on the method in Olkin and Finn (1995).<sup>26</sup> As lesser teams adapted to the new rules in 2015, the driver share of variation dropped further to a low of 9.88%<sup>27</sup>, while the interaction plus team shares increased to 62.1%<sup>28</sup>.

Regardless of the rule changes, the driver share of the total variation in rank finishes is consistently the smallest share in Table 6. The interaction between driver and team consistently accounts for the largest share of variation, excepting the 2012 season in which the unexplained

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<sup>25</sup> The Kinetic Energy Recovery System (KERS) that charges electric batteries in the cars using braking was first required in the 2009 F1 season. However, fuel consumption was poor at 194 kg/hour due to the much larger V-10 engines. The 2014 turbo-hybrid system consumed only 100 kg/hour, allowing for a smaller, lighter fuel tank.

<sup>26</sup> The 2012 and 2014 driver's shares are significantly different at 90% confidence. The team shares for 2012 and 2014 are not significantly different at any reasonable level of confidence, however the results are suggestive. A useful calculator for confidence intervals can be found at <https://ptenklooster.nl/confidence-interval-calculators/confidence-intervals-for-r-square/>

<sup>27</sup> Significantly different from the 2012 value at 95% confidence.

<sup>28</sup> Significantly different from the 2012 value at 95% confidence.

share is the largest. By itself, this shared variation between driver salary and team budget (not including driver salaries) does not imply these are complimentary inputs since they could be negatively associated with each other, even though the association is strong. A negative association suggests these inputs are substitutes, which could certainly be the case if total team spending (budgets and salaries) is limited. The correlation coefficient between driver salaries and team budgets ranges between 0.574 and 0.799 in our sample. Better drivers and better teams appear to be significantly complimentary inputs into the production function that produces rank finishes. Drivers do not just drive the cars but also provide valuable input and feedback on the development of the cars. Their labor is a sort of endogenous growth process that improves the technology of capital. This then feeds back into the productivity of the driver. Lesser drivers and teams do not experience this endogenous process to as great a degree.

One can use the estimates in Tables 7-10 to suggest how F1 teams should target their scarce resources. The marginal effect of driver salary on rank finish is given from the combined regression model (equation 3) by  $\frac{\gamma_5}{salary_j} + \left[ \left( \frac{\gamma_{10}}{salary_j} \right) \times lnteamexp_i \right]$  where  $\gamma_{10}$  is the estimated coefficient for the interaction term between driver salaries and team expenditures. This calculation is provided for the 2012-19 F1 seasons in Table 11 in the first three rows under the row titled Driver. The average driver salary is used for each season, while the table provides the computations for the maximum, minimum and average team budgets. For example, the effect of a \$1 million increase in driver salary evaluated at the average team budget in 2019 is an improvement in rank finish by 0.1298 positions, however the rank position improves by 0.0252 positions evaluated at the highest team budget, while improving by 4.177 positions for the lowest team budget. Interpreted another way, it would take an increase of  $1/0.1298 = \$7.7$  million in driver salary to improve the rank finish by one position for a team at the average team budget in



2019. That is a hefty increase in salary for the average team. The results vary by season, but generally the smaller budget teams benefit the most from increasing the driver salary with the effect diminishing as the team budget increases to the maximum budget. Increasing the driver salary always improves the rank position regardless of team budget when evaluated at the average team budget, excepting for the 2012 season. The marginal effect at the minimum team budget is very sensitive to actual rank finishes in the season. An unexpected podium finish for a low budget team with a mid-to high salaried driver can distort the marginal effect significantly in favor of spending more money on a good driver.

<Table 11 inserted here>

Table 11 also reports the estimated marginal effect of the team budget on rank finish (under the row labelled Team),  $\frac{\gamma_1}{teamexp_i} + \left[ \left( \frac{\gamma_{10}}{teamexp_i} \right) \times lnsalary_j \right]$ , evaluated at the average team budget and maximum, minimum and average driver salaries, for the 2012-19 F1 seasons. For example, a \$1 million increase in the team budget is predicted to improve the rank finish by 0.0062 positions when evaluated at the average driver salary, but a worsening of 0.063 positions when evaluated at the minimum driver salary. It would take a  $1/0.0062 = \$161.3$  million increase in team budget to improve the rank finish by one position for a team paying the average driver salary in 2019. That is a considerable increase. Generally, the marginal effect of the team budget is smaller than the driver salary evaluated at the averages of each. Teams already at the maximum budget or driver salaries have the smallest marginal effects, however the smallest budget or driver salaries teams (generally these are the same teams) have unpredictable marginal effects on the rank finish.

Although the driver share of the variation in rank finishes is small, the marginal effect of paying a driver a higher salary is relatively large. It is likely that a higher salary coincides with a more talented driver that offers a greater promise of podium finishes. If true, one could say that the marginal product of drivers is high, even though driving skill offers only a small share of total output.

## SUMMARY

F1 racing could easily be the most capital intensive and technologically advanced “sport” in the world. Highly skilled drivers compete in complex racing machines that are difficult to master. This paper asks two questions: What are the shares of racing results attributable to driver skill and team technology? How should teams invest their scarce budgets in these two inputs? The simple 80-20 rule is found to be an over-simplification of the shares. Our regression results for the 2012-19 F1 seasons suggest driver skill and team technology uniquely contribute roughly 15% and 20% respectively to race outcomes (rank finishes), but that the interaction between the two complementary inputs accounts for between 30% and 40%. More skilled drivers improve the return to team technology and vice-versa. After all, F1 cars do not drive themselves and drivers cannot ply their trade without an F1 car. The random share of race outcomes is significant at 20-35%. Perhaps F1 world champion Nico Rosberg can be excused for ignoring the random component in his casual assessment of the shares, however ratio-scaling the shares still amounts to a roughly 22-30-50% split between driver, team and driver-team interaction. To say that drivers contribute only 20% is a vast underestimate given the critical complementarity between driver and team. Drivers do not just drive cars, but also provide valuable input into car

development and testing. Our results broadly agree with Bell (2016) who utilizes what is essentially a two-factor ANOVA approach.

Where F1 teams best invest their scarce financial resources can only be determined by incorporating team budgets and driver salaries into our regression models. We allowed for an interaction effect, essentially a shift in the marginal product of the driver skill (team budget) when the team budget (driver skill measured by salary) is increased. Although teams must spend large amounts to field even minimally competitive cars in F1, our results suggest that the return to hiring more driving skill (at an assumedly higher driver salary) is positive but diminishing in the size of the team budget. The return to spending more on the team budget is positive but diminishing in the size of the driver salary (assumedly driver skill). The upshot is that teams that spend more team budgets and driver salaries will improve their rank finishes, but at a diminishing rate. This suggests an interesting maximization problem for a representative F1 team that we leave for future research (and more data).

Appendix: Data sources

Variable name	Description	Source
$teamexp_i$	Annual total team expenditures excluding driver salaries (US \$)	2019: <a href="https://beyondtheflag.com/2019/11/06/formula-1-current-team-budgets-175m-cap-impending/">https://beyondtheflag.com/2019/11/06/formula-1-current-team-budgets-175m-cap-impending/</a> 2018: <a href="https://www.racefans.net/2018/12/19/how-much-f1-teams-spent-race-2018-part-one/">https://www.racefans.net/2018/12/19/how-much-f1-teams-spent-race-2018-part-one/</a> 2017: <a href="https://www.grandprix247.com/2017/07/05/mclaren-spend-e225-million-to-score-two-points/">https://www.grandprix247.com/2017/07/05/mclaren-spend-e225-million-to-score-two-points/</a> 2016: <a href="https://thenewswheel.com/what-did-formula-1-teams-spend-in-2016/">https://thenewswheel.com/what-did-formula-1-teams-spend-in-2016/</a> 2015: <a href="https://motortrivia.com/2015/motorsport-04/678-F1-team-budget-2015.html">https://motortrivia.com/2015/motorsport-04/678-F1-team-budget-2015.html</a> 2014: <a href="https://bleacherreport.com/articles/2281654-mercedes-and-williams-were-the-most-efficient-teams-in-the-2014-formula-1-season">https://bleacherreport.com/articles/2281654-mercedes-and-williams-were-the-most-efficient-teams-in-the-2014-formula-1-season</a> 2013: <a href="https://forums.autosport.com/topic/182862-mclarens-finances-split/page-8">https://forums.autosport.com/topic/182862-mclarens-finances-split/page-8</a> 2012: <a href="https://www.f1technical.net/forum/viewtopic.php?t=10259">https://www.f1technical.net/forum/viewtopic.php?t=10259</a>
$salary_i$	Annual driver salary (US \$)	Various issues of: <a href="https://www.crash.net/f1/news/">https://www.crash.net/f1/news/</a>
$devpittime_{i,n}$	Deviation of fastest pit stop time from average fastest time across all teams	Various issues of: <a href="https://www.racefans.net/">https://www.racefans.net/</a>
$racestarts_{i,n}$	Number of F1 race starts by driver prior to current race	Computed by authors from: <a href="https://www.f1-fansite.com">https://www.f1-fansite.com</a>
$teamdnf_{i,j,n}$	Dummy variable for car not finishing race due to team error	Computed by authors from: <a href="https://www.f1-fansite.com">https://www.f1-fansite.com</a>
$driverdnf_{i,n}$	Dummy variable for car not finishing race due to driver error	Computed by authors from: <a href="https://www.f1-fansite.com">https://www.f1-fansite.com</a>
$poll_{i,j,n}$	Poll position of driver at start of race	<a href="https://www.f1-fansite.com">https://www.f1-fansite.com</a>
$rankfinish_{i,j,n}$	Finish position of each driver at end of race	<a href="https://www.f1-fansite.com">https://www.f1-fansite.com</a>

Driver	Team	Driver Compensation (US\$)	Team Expenses (US\$)
Lewis Hamilton	Mercedes	57,000,000	415,000,000
Valteri Bottas	Mercedes	12,000,000	415,000,000
Sebastian Vettel	Ferrari	45,000,000	414,500,000
Charles Leclerc	Ferrari	3,500,000	414,500,000
Max Verstappen	Red Bull	13,500,000	430,100,000
Pierre Gasly	Red Bull	1,400,000	430,100,000
Kevin Magnussen	Haas	1,200,000	266,000,000
Romain Grosjean	Haas	1,800,000	266,000,000
Nico Hulkenberg	Renault	4,500,000	250,500,000
Daniel Ricciardo	Renault	17,000,000	250,500,000
Kimi Raikkonen	Alfa Romeo	4,500,000	136,270,000
Antonio Giovinazzi	Alfa Romeo	230,000	136,270,000
Lance Stroll	Racing Point	1,200,000	166,300,000
Sergio Perez	Racing Point	3,500,000	166,300,000
Daniil Kyvat	Toro Rosso	300,000	137,530,000
Alexander Albon	Toro Rosso	170,000	137,530,000
Lando Norris	McLaren	260,000	184,440,000
Carlos Sainz	McLaren	3,300,000	184,440,000
George Russell	Williams	180,000	131,250,000
Robert Kubica	Williams	570,000	131,250,000

**Table 1.** Driver compensation and team expenses, 2019 Formula 1 season.

Sources: <https://beyondtheflag.com/2019/11/06/formula-1-current-team-budgets-175m-cap-impending/> and <https://www.spotrac.com/formula1/2019/>.

Car Parts	Price
Front wing:	\$150,000
Halo	\$17,000
Set of tires	\$2,700
Steering wheel	\$50,000
Engine Unit	\$10.5 million
Fuel Tank	\$140,000
Carbon Fibre (Chassis)	\$650,000 – \$700,000
Hydraulics	\$170,000
Gearbox	\$4,00000
Rear wing	\$85,000
Total Car Cost	\$12.20 million

**Table 2.** Cost of components for typical 2020 F1 race car.

Source: <https://thesportsrush.com/f1-news-f1-car-cost-how-expensive-are-the-formula-1-cars-which-teams-spend-the-most-on-their-cars/>

	F1 Season									
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Gini	0.795	0.831	0.763	0.811	0.818	0.811	0.821	0.820	0.812	0.814
S.E.	0.0760	0.063	0.066	0.074	0.077	0.058	0.065	0.062	0.060	0.060

**Table 3.** Gini coefficient by season for Driver's Championship points.

Source: <https://www.f1-fansite.com/f1-results> and author's calculations. See Davidson (2009) for formulae.

	F1 Season									
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Gini	0.390	0.410	0.371	0.396	0.401	0.401	0.407	0.404	0.446	0.402
S.E.	0.161	0.173	0.151	0.166	0.167	0.163	0.169	0.168	0.168	0.165

**Table 4.** Gini coefficient by season for Constructor's Championship points.

Source: <https://www.f1-fansite.com/f1-results> and author's calculations. See Davidson (2009) for formulae.



Driver	Season/Team/Finish	Season/Team/Finish
Kiki Rosberg	1981/Fittipaldi/36	1982/Williams/1
Niki Lauda	1983/McLaren/10	1984/McLaren/1
Elio de Angelis	1983/Lotus/18	1984/Lotus/3
Nigel Mansell	1987/Williams/2	1988/Lotus/9
Nelson Piquet	1985/Brabham/8	1987/Williams/1
Rubens Barichello	1993/Jordan/19	1994/Jordan/6
Heinz Harold-Frentzen	1996/Sauber/12	1997/Williams/2
Damon Hill	1996/Williams/1	1997/Arrows/12
Jean Alesi	1997/Benetton/4	1998/Sauber/11
Jensen Button	2001/Benetton/17	2002/Renault/7
Jensen Button	2002/Renault/7	2004/BAR/3
Felipe Massa	2005/Sauber/13	2006/Ferrari/3
Jensen Button	2008/Honda/18	2009/Brawn/1
Rubens Barichello	2008/Honda/18	2009/Brawn/3
Fernando Alonso	2009/Renault/9	2010/Ferrari/2
Rubens Barichello	2010/Ferrari/2	2011/Williams/10
Daniel Riccardo	2013/Toro Rosso/14	2014/Red Bull/3
Valtteri Bottas	2016/Williams/8	2017/Mercedes/3
Charles Leclerc	2017/Sauber/13	2018/Ferrari/4

**Table 5.** Notable driver standing changes, 1980-2019.

Season	SST	$R^2(\text{step 1})$	$R_D^2$	$R_{TD}^2$	$R_T^2$	$1 - R_D^2 - R_{TD}^2 - R_T^2$
2019	13965	0.5719	0.1264	0.3956	0.1763	0.3017
2018	13965	0.6109	0.1677	0.3260	0.2849	0.2214
2017	13300	0.5160	0.2007	0.2855	0.2305	0.2833
2016	18595	0.6000	0.1206	0.4097	0.1903	0.2794
2015	12887	0.6196	0.0988	0.4228	0.1968	0.2816
2014	14193	0.6210	0.1152	0.3948	0.2262	0.2638
2013	16954	0.6240	0.1021	0.4755	0.1485	0.2739
2012	22964	0.4831	0.1670	0.2841	0.1990	0.3499

**Table 6.** Variation in rank finishes explained by driver, team, interaction and unexplained. 2012-2019 F1 seasons.

Coefficient	2019			2018		
	OLS	Censored	Marginals	OLS	Censored	Marginals
<i>Constant</i>	6.278**	5.217		15.690*	13.025*	
<i>lnteamexp<sub>i</sub></i>	-0.420	-0.254	-0.253	-1.544**	-1.017**	-1.016**
<i>devpittime<sub>i,n</sub></i>	0.463*	0.577*	0.574*	0.006	0.027	-0.027
<i>teamdnf<sub>i,j,n</sub></i>	8.236*	9.064*	9.022*	8.899*	9.543*	9.536*
<i>poll<sub>i,j,n</sub></i>	0.404*	0.416*	0.414*	0.304*	0.318*	0.312*
<i>lnsalary<sub>i</sub></i>	1.328	2.265	2.254	5.303*	6.797*	6.719*
<i>racestarts<sub>i,n</sub></i>	0.026*	0.028*	0.028*	-0.026*	-0.028*	-0.028*
<i>racestarts<sub>i,n</sub><sup>2</sup></i>	-5.24e <sup>-5</sup> *	-5.91e <sup>-5</sup> *	-5.88e <sup>-5</sup> *	7.12e <sup>-5</sup> *	8.01e <sup>-5</sup> *	8.00e <sup>-5</sup> *
<i>driverdnf<sub>i,n</sub></i>	9.302*	10.400*	10.351*	8.726*	9.415*	9.408*
<i>lnS<sub>i</sub> * lnB<sub>j</sub></i>	-0.423**	-0.610*	-0.608*	-1.041*	-1.343*	-1.342*
<i>R<sup>2</sup></i>	0.706	0.718		0.788	0.802	
<i>N</i>	420	420		420	420	

**Table 7.** Least squares and censored coefficient estimates for the combined regression model, 2018-19 F1 seasons. \* denotes statistical significance at 95% confidence. \*\* denotes statistical significance at 90% confidence.

Coefficient	2017			2016		
	OLS	Censored	Marginals	OLS	Censored	Marginals
<i>Constant</i>	11.980*	10.800*		12.700*	12.140*	
<i>ln</i> teamexp <sub>i</sub>	-0.815*	-0.619**	-0.617**	-1.123*	-1.035*	-1.032*
<i>dev</i> pittime <sub>i,n</sub>	0.016	-0.032	0.032	-6.26e <sup>-4</sup>	-0.001	-0.001
<i>team</i> dnf <sub>i,j,n</sub>	8.286*	8.707*	8.679*	8.602*	9.067*	9.039*
<i>poll</i> <sub>i,j,n</sub>	0.263*	0.279*	0.275*	0.278*	0.443*	0.442*
<i>ln</i> salary <sub>i</sub>	0.864	1.766	1.760	2.217*	2.856*	2.847*
<i>race</i> starts <sub>i,n</sub>	-0.030*	-0.031*	-0.032*	-0.036*	-0.039*	-0.039*
<i>race</i> starts <sub>i,n</sub> <sup>2</sup>	1.16e <sup>-4</sup> *	1.22e <sup>-5</sup> *	1.22e <sup>-4</sup> *	1.33e <sup>-4</sup> *	1.46e <sup>-4</sup> *	1.45e <sup>-4</sup> *
<i>driver</i> dnf <sub>i,n</sub>	8.809*	9.462*	9.432*	9.115*	10.110*	10.074*
<i>ln</i> S <sub>i</sub> * <i>ln</i> B <sub>j</sub>	-0.283	-0.462**	-0.460**	-0.436*	-0.567*	-0.566*
<i>R</i> <sup>2</sup>	0.730	0.748		0.725	0.744	
<i>N</i>	400	400		400	400	

**Table 8.** Least squares and censored coefficient estimates for the combined regression model, 2016-17 F1 seasons. \* denotes statistical significance at 95% confidence. \*\* denotes statistical significance at 90% confidence.

Coefficient	2015			2014		
	OLS	Censored	Marginals	OLS	Censored	Marginals
<i>Constant</i>	10.855*	10.200*		15.160*	14.890*	
<i>ln</i> teamexp <sub><i>i</i></sub>	-1.053*	-1.066*	-1.063*	-2.170*	-2.179*	-2.176*
<i>dev</i> pittime <sub><i>i,n</i></sub>	0.421*	0.434*	0.433*	-0.010	-0.004	-0.004
<i>team</i> dnf <sub><i>i,j,n</i></sub>	7.426*	8.112*	8.093*	8.539*	8.994*	8.979*
<i>poll</i> <sub><i>i,j,n</i></sub>	0.420*	0.458*	0.457*	0.331*	0.359*	0.359*
<i>ln</i> salary <sub><i>i</i></sub>	1.649	2.036**	2.030*	-2.873*	-2.722*	-2.717*
<i>race</i> starts <sub><i>i,n</i></sub>	-0.013	-0.007	-0.007	-0.002	-0.005	-0.005
<i>race</i> starts <sub><i>i,n</i></sub> <sup>2</sup>	6.90e <sup>-5**</sup>	6.31e <sup>-5**</sup>	6.23e <sup>-5**</sup>	3.96e <sup>-5</sup>	5.65e <sup>-5</sup>	5.64e <sup>-5</sup>
<i>driver</i> dnf <sub><i>i,n</i></sub>	7.670*	8.257*	8.232*	9.380*	10.260*	10.239*
<i>ln</i> S <sub><i>i</i></sub> * <i>ln</i> B <sub><i>j</i></sub>	-0.364**	-0.462*	-0.460*	0.497*	0.463*	0.462*
<i>R</i> <sup>2</sup>	0.730	0.739		0.752	0.777	
<i>N</i>	380	380		352	352	

**Table 9.** Least squares and censored coefficient estimates for the team regression model, 2014-15 F1 seasons. \*denotes statistical significance at 95% confidence. \*\*denotes statistical significance at 90% confidence.

Coefficient	2013			2012		
	OLS	Censored	Marginals	OLS	Censored	Marginals
<i>Constant</i>	11.840*	12.000*		23.020*	21.750*	
<i>ln</i> teamexp <sub><i>i</i></sub>	-1.209*	-1.385*	-1.382*	-3.108*	-2.909*	-2.887*
<i>dev</i> pitttime <sub><i>i,n</i></sub>	0.048	0.007	0.007	1.131*	1.181*	1.172*
<i>team</i> dnf <sub><i>i,j,n</i></sub>	9.645*	10.710*	10.680*	10.011*	11.020*	10.939*
<i>poll</i> <sub><i>i,j,n</i></sub>	0.407*	0.423*	0.421*	0.287*	0.318*	0.316*
<i>ln</i> salary <sub><i>i</i></sub>	-0.964	-0.558	-0.557	2.642**	3.233*	3.208*
<i>race</i> starts <sub><i>i,n</i></sub>	-0.009	-0.011	-0.011	-0.015	-0.019	-0.019
<i>race</i> starts <sub><i>i,n</i></sub> <sup>2</sup>	3.48e <sup>-5</sup>	5.42e <sup>-5</sup>	5.41e <sup>-5</sup>	5.60e <sup>-5</sup>	7.06e <sup>-5</sup>	7.00e <sup>-5</sup>
<i>driver</i> dnf <sub><i>i,n</i></sub>	8.785*	10.475*	10.444*	10.490*	11.310*	11.225*
<i>ln</i> S <sub><i>i</i></sub> * <i>ln</i> B <sub><i>j</i></sub>	0.093	-0.027	-0.027	-0.488**	-0.605**	-0.600**
R <sup>2</sup>	0.730	0.747		0.656	0.679	
N	418	418		480	480	

**Table 10.** Least squares and censored coefficient estimates for the combined regression model, 2012-13 F1 seasons. \* denotes statistical significance at 95% confidence. \*\* denotes statistical significance at 90% confidence.

	2012	2013	2014	2015	2016	2017	2018	2019
Driver								
Max budget	-0.0032	-0.0352	-0.0083	-0.0252	-0.0162	-0.0266	-0.0173	-0.0252
Min budget	3.8343	-4.3625	-4.8605	-0.2741	2.6182	-2.8437	3.0670	-4.177
Average budget	0.0316	-0.1499	-0.0792	-0.0600	-0.0321	-0.1122	-0.0256	-0.1298
Team								
Max salary	-0.0200	-0.0063	-0.0031	-0.0052	-0.0071	-0.0051	-0.0191	-0.0063
Min salary	-0.0303	-0.0376	-0.0811	-0.0030	0.0012	0.0022	0.0137	0.0063
Average salary	-0.0278	-0.0140	-0.0123	-0.0078	-0.0092	-0.0057	-0.0219	-0.0062

**Table 11.** Effect of a \$1 million increase in driver salary (team budget) on improvement in rank finish evaluated at minimum, maximum and average team budget (driver salary), 2012-19 F1 seasons.

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