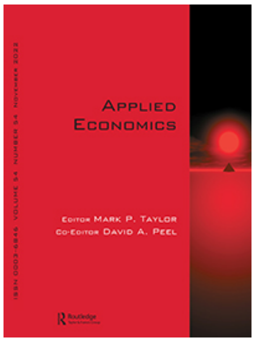

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Race to the podium: separating and conjoining the car and driver in F1 racing

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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 fixed effects FGLS 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.

KEYWORDS

Formula one; complimentary inputs; drivers; technology

JEL CLASSIFICATION

L83; D24; Z21

I. 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[1] 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 racetracks 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.[2] 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.[3] Off the track the race is composed of the teams spending large amounts of 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

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[1]As opposed to oval track racing, such as the NASCAR circuit in the United States.

[2]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.

[3]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, Rosseger, and Mantel (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.

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.[4] 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.[5] This result confirms the assertion using a qualitative analysis by Aversa, Santi, and Haefliger (2015) that F1 teams that develop technologies and develop skilled drivers perform better than teams that focus on only one of these strategies. However, a significant unexplained (and possibly random) 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).

II. 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.[6] 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.[7] Similarly, driver compensation is not made publicly available. Table 1 below provides estimates of team expenses and driver compensation for the 2019 F1 season.

Drivers and teams earn points for finishes in the top ten positions on a rapidly declining scale.[8] The highest point finishers at the end of the racing season are declared the driver world 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.[9] 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 totalled 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. These bonus payments are asymmetric and favour the

[4]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.

[5]Increases in the stock of team quality increases the marginal product of driver quality and vice-versa. Evidence for this is found by use of an interaction variable in the regression model to follow.

[6]The first F1 season in 1950 featured only 7 races, increasing to 16 races by the 1984 season. The 2020 season featured 21 races.

[7]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.

[8]First place finishers earn 25 points, while the 10th 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.

[9]https://www.totalsportek.com/f1/formula-one-prize-money/.

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

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

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

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

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

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

larger, better performing teams, to the detriment of smaller teams. Budzinski and Muller-Kock (2018) suggest that the bonus payment system warrants antitrust investigation, although an investigation was dismissed in 2015 (Sylt 2015). 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.

The technologies contained in a modern F1 race car are expensive. The standard 1.6 litre 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.

Driver compensation is considerable, but its distribution is highly skewed, as evidence 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.[10] 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. Mastromarco and Runkel (2009) consider the effects of rule changes on competitive balance in F1 using an extensive sample from 1950 to 2005. They find that rule changes reduce team performance but improve competitive balance, resulting in a net increase in revenue for the FIA. Judde, Booth, and Brooks (2013) find evidence to suggest that the recent regulations that restrict team budgets should improve competitive balance and increase television revenue for the FIA. Schreyer and Torgler (2018) provide statistical evidence for 1993–2014 that greater competitive balance increase TV viewership in F1.

Competitive balance is ultimately the outcome of the interaction between the skills of F1 drivers and the quality of their cars. 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

[10]There are numerous references. See Lazear and Rosen (1981) or Nalebuff and Stiglitz (1983) to name two.

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

	F1 Season									
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
# Drivers	24	24	24	22	22	20	20	20	22	20
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

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

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

	F1 Season									
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
# Teams	12	12	12	11	11	10	10	10	11	10
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

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

there is very little parity in the driver point totals, with the top few drivers earning the bulk of the points.

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 appear in Table 4 and 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 year over year as no Gini coefficient 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.

III. 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. 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 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.

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 (Judde, Booth, and Brooks (2013) and others). 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.

IV. 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 task is to estimate each of these components. 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 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 assigns points according to their own scale.

Some variables that capture the quality of the car and team, and the skill of the driver are available from various F1 websites (variable sources are given in an appendix). 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.[11] 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 real team expenditures (*lnteamexp*) excluding driver salaries as an explanatory variable.[12] We compiled these estimates from a variety of sources listed in the appendix. We chose the deviation of the average pit stop time for each team from the race average pit stop time (*devpittime*) as an important determinant of rank finish. Deviations of mere seconds can have great effects on the rank finish (the average pit stop time differs for each race due to the overall length of the pit lane).[13] 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.[14] 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 (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.[15] However, the unique structure to the racing season in F1 made the inconclusion 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 essentially the number of cars that drop out of the race.[16] 1 summarizes the regression model relating team performance to rank finish.

$$\begin{aligned} rankfinish_{i,j,n} = \alpha &+ \beta_1 lnteamexp_i \\ &+ \beta_2 devpittime_{i,n} + \beta_3 teamdnf_{i,j,n} \\ &+ \beta_4 poll_{i,j,n} + e_{i,j,n} \end{aligned} \tag{1}$$

[11]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.

[12]Recent 2021 rule changes limit overall team spending to $145 million but exclude driver salaries and several other expenditures (Boll 2021), so it remains to be seen if it will change the impact of team spending on outcomes. Team expenditures were converted to US Dollars at the average Euro/Dollar exchange rate for each F1 season if the team expenditure was quoted in Euros instead of US Dollars. These team expenditures were then deflated using the average US CPI for each F1 season.

[13]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.

[14]Wesselbaum and Owen (2021) find that being on the pole position increases the probability of finishing first in the race by almost 10% using a logit regression model and F1 results from 1950–2013. This translates to finishing two positions higher using a Poisson regression model.

[15]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.

[16]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.

The structure of the regression panel 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. Each season is a panel dataset with the cross-section units being the drivers and the 'time' units being the races. The rank finish and values for the independent variables were stacked for each driver for all races in a season, thus resulting in a matrix partitioned by drivers. Fixed effects were included for the driver effects, but not for the race effects since the average rank finish for all drivers is the same for each race, given the same number of drivers in each race.[17]

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) 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 real salary (*lnsalary*) paid to each driver as a measure of the driver's historical marginal revenue product.[18] 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 (crash typically) were captured by a dummy variable (*driverdnf*). Drivers were not distinguished by team in the driver regression model since the team expenditure variable was not included, hence the subscript k for each driver is not limited to $k = 1, 2$ as was the case for the subscript j in the team regression model, rather it indexes the total number of drivers in a race. Fixed effects were included for driver effects.[19] Descriptive statistics for all of the variables appear in Table 5.

$$\begin{aligned} rankfinish_{k,n} = \delta &+ \theta_1 lnsalary_k + \theta_2 racestarts_{k,n} \\ &+ \theta_3 racestarts^2_{k,n} + \theta_4 driverdnf_{k,n} \\ &+ \theta_5 poll_{k,n} + u_{k,n} \end{aligned} \tag{2}$$

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 3. We included an additional independent variable that is the interaction between the driver salary and the team budget (*interact* = *lnsalary*lnteamexp*) 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 levels.

$$\begin{aligned} rankfinish_{i,j,n} = \alpha &+ \beta_1 inteamexp_i \\ &+ \beta_2 devpittime_{i,n} + \beta_3 teamdnf_{i,j,n} \\ &+ \beta_4 poll_{i,j,n} + \beta_5 insalary_i \\ &+ \beta_6 racestarts_{i,n} + \beta_7 racestarts^2_{i,n} \\ &+ \beta_8 driverdnf_{i,n} + \beta_9 \mathrm{interact}_{i,j} \\ &+ v_{i,j,n} \end{aligned} \tag{3}$$

When driver and team performance is measured by the rank finish in each race, one should have a strong suspicion that cross-sectional dependence could result in inefficient estimates when using fixed effects. If one driver finishes unexpectedly high in the

[17]A random effects model is sometimes used when the sample of driver results is randomly drawn from a population of driver results, hence an additional error term is included for the randomness of the draw. Since our sample included the entire population of F1 drivers for each season, a fixed effects model is appropriate.

[18]Driver salaries were converted to US Dollars at the average Euro/Dollar exchange rate for each F1 season if the salary was quoted in Euros instead of US Dollars. These salaries were then deflated using the average US CPI for each F1 season.

[19]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 employed a censored regression model that combines (1) and (2) with the assumption of normally distributed errors, but did not obtain estimates that differed even marginally from the fixed effects estimates.

Table 5. Descriptive statistics for variables in (1), (2) and (3). 2012–2019 F1 seasons.

Variable	Mean	Standard Deviation	Variance	Minimum	Maximum
rankfinish	11. 15,576	6. 200,933	38. 45,156	1	24
salary	7. 860,818	12.03486	144.8378	0.136	60
teamexp	196.8553	128.8621	16,605.44	35.5	517.26
pollpos	11. 15,126	6. 192,687	38. 34,937	1	24
driverdng	0.066927	0. 249,933	0.062466	0	1
teamdnf	0. 114,046	0. 317,914	0. 10,107	0	1
driverstarts	102.9745	82. 78,251	6852.944	1	328
devpittime	−0.01323	34. 10,175	1162.929	−133.554	1324.026
interact	4. 933,276	9. 176,697	84. 21,177	−9. 29,674	24. 37,264

order of finish, other drivers could finish unexpectedly low, resulting in a significant correlation in the errors for each driver in each race. Cross-sectional dependence is classified as strong dependence when the cross-section units (drivers) are subject to identical common shocks, whereas shocks that are correlated across cross-section units, but are not common, are classified as weakly dependent (Sarafidis and Wansbeek 2012). Strong dependence would imply that an unexpected positive shock is common to all drivers, impossible when the measure of performance is rank finish. All drivers cannot improve their rank finish – some will improve at the expense of the rest falling. Weak dependence can be incorporated using an FGLS (feasible generalized least squares) method that results in efficient coefficient estimates. The method estimates the variance-covariance matrix of residuals across drivers in the same race for all races in a season, then uses this matrix to adjust the standard errors of the slope coefficients to incorporate any cross-sectional covariance, essentially the same as a SURE.[20] We test for cross-sectional dependence using Pesaran's CD test (Pesaran 2021) that relies on an estimate of the average correlation coefficient across combinations of cross-section units (drivers) at the same point in time (races).[21]

The procedure 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 is straightforward. The procedure is to:

(1) Compute the total variation in the *rankfinish* variable across the K teams and N races in a single season, $SST = \sum_{i=1}^{K}\sum_{n=1}^{N}\left(Y_{i,n} - \bar{\bar{Y}}\right)^2$.
(2) Estimate the team regression model in (2), compute the R^2 and compute the residuals.[22]
(3) Use the residuals from step 2 as dependent variable in the regression of the driver model in (1) and compute the explained variation, $SSR = \sum_{i=1}^{K}\sum_{j=1}^{2}\sum_{n=1}^{N}\left(\hat{e}_{i,j,n} - \bar{\bar{e}}\right)^2$. The percentage of variation in *rankfinish* attributable to the driver alone is $R_D^2 = SSR/SST$ (SST computed from step 1).[23]
(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 $R_T^2 = R^2(step1) - R_{TD}^2$.
(6) The unexplained variation in *rankfinish* is computed as $1 - R_T^2 - R_{TD}^2 - R_D^2$.

[20] The plm package in the R statistical software includes this FGLS method. A good reference for FGLS using R can found at https://cran.r-project.org/web/packages/plm/vignettes/A_plmPackage.html.
[21] The CD statistic is normally distributed.
[22] The choice of R^2 measure is not obvious in a fixed effects model. We chose to use the "within" measure which computes the R^2 between the de-meaned dependent variable and the explanatory variables. As we show later, the choice really makes no difference since the inclusion of fixed effects contributed marginally to the regression results.
[23] 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.

This procedure is first applied to a regression model that pools the season panels together into a single unbalanced panel for Equations (1), (2) and the combined model (3). This pooled panel for the 2012–19 F1 seasons includes instances of 170 drivers and 157 races. Many of the drivers compete in more than one F1 season, however we treated each instance of a driver as a unique individual since they are separated by time. Following this, Equation (1), (2) and the combined model (3) were estimated separately for each season to investigate any effects of rule changes that we discuss in a later section.

V. Results

The fixed effects FGLS regression coefficient estimates of the team, driver and combined regression model in (1), (2) and (3) for the pooled 2012–19 F1 seasons appear in Table 6. The table also includes the de-meaned R^2, F-test for the significance of the fixed effects, and the Pesaran (2021) CD test for cross-sectional dependence. The statistical significance of the fixed effects could not be rejected in each model, nor the statistical significance of cross-sectional dependence.

Most of the estimated coefficients are statistically significant at 95% confidence in the 2012–19 regression models, with the exception of the pit time deviations and driver salary in the combined panel model. The strong significance of the coefficients suggests that multicollinearity of the independent variables is not an issue.[24] We suspect that the *lnsalary* variable is statistically insignificant in the combined panel model due to its strong correlation with the *lnteamexp* variable ($r = 0.6305$). In fact, regressing the driver panel model without the team expenditures variable moved the *lnsalary* variable to statistical significance. The effect on the rank finish of a \$1 million increase in the average real team budget is given by $\frac{-0.922}{teamexp} - \frac{-0.13}{teamexp} ln\left(\overline{salary}\right)$. Clearly moving up to the winner's podium in F1 comes at a considerable increase in the team budget. For example, a team that consistently finishes tenth in the rank finish in each race and is positioned at the average team budget (\$195.86 million) and average driver salary (\$7.86 million) needs to increase its team budget by an estimated \$164.6 million $[(-1/\left(\frac{-0.922}{195.86} - \frac{-0.13}{195.86}\ln(7.86)\right).)]$ to finish in ninth place consistently over the 2012–19 sample period, holding all other variables constant. The necessary spending varies each season, largely due to differences in the average team budgets and driver salaries. The amount also varies according to the existing team budget and driver salary due to the non-linearity of the relationship between expenditures and rank finish. For instance, at the 75th percentile of team budget and driver salary, \$260 million and \$10.1 million respectively for the 2012–19 sample period, the team budget needs to increase by an estimated \$212.7 million.

Table 6. FGLS coefficient estimates for the combined regression model, team and driver regression models, pooled 2012–19 F1 seasons. *denotes statistical significance at 95% confidence.

	2012-19 combined panel model (3)		2012-19 team panel model (1)		2012-19 driver panel model (2)	
Coefficient	FGLS	Z value	FGLS	Z value	FGLS	Z value
$Constant$	10.083	55.34*	12.334	39.63*	5.768	80.03*
$lnteamexp_i$	−0.922	−26.56*	−1.496	−26.71*		
$devpittime_{i,n}$	$-4.71\text{x}10^{-4}$	−1.354	$-2.46\text{x}10^{-4}$	−2.11*		
$teamdnf_{i,j,n}$	8.611	517.47*	7.871	251.82*		
$poll_{i,j,n}$	−0.414	−299.15*	−0.487	−173.73*	−0.497	−139.05*
$lnsalary_i$	0.095	0.93			−0.719	34.50*
$racestarts_{i,n}$	$-4.77\text{x}10^{-3}$	−6.69*			$-7.87\text{x}10^{-3}$	−8.14*
$racestarts^2_{i,n}$	$3.14\text{x}10^{-5}$	14.75*			$4.12\text{x}10^{-5}$	13.87*
$driverdnf_{i,n}$	9.146	521.01*			7.937	127.57*
$interact_{i,j}$	−0.130	−7.05*				
R^2	0.7024		0.5563		0.5051	
N	3,332		3,332		3,332	
F	2.935*		2.432*		4.403*	
$CD\ (Z)$	−4.439*		−2.807*		−2.707*	

[24]The correlation coefficient between lnsalary and devpittime is 0.0256.

A team at the 25th percentile ($113 million and $0.52 million respectively) needs to increase its team budget by an estimated $135 million, still a considerable sum.

Teams can also contribute to better performances by reducing the average pit stop time. Pit stops are very short in F1 racing, typically around 2.5 to 3 seconds while the car is stopped. Small improvements can have a large effect on track position. While not statistically significant in the combined panel model, deviations from the average pit time have a significantly negative effect in the team panel model, suggesting the counter-intuitive result that longer pit times improve the rank finish. This could be the result of teams that are far ahead during the race having the luxury of somewhat longer pit stops, however we cannot confirm this.

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 0.414 positions using the combined panel model. Establishing a good poll position relies heavily on the speed and handling of the car at full speed with no obstacles, 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.

Of course, a good finish result cannot be obtained if the car does not finish the race due to a team-related issue. The coefficient for the *teamdnf* variable suggests that not finishing the race results in an average loss of 8.166 positions in rank finish.

Evaluated at the average driver $8.56 million salary for the 2012–19 seasons, a $1 million increase in the driver's salary[25] results in an improvement in the rank finish equal to $\frac{0.095}{7.86} - \left(\frac{0.13}{7.86} \times ln(195.86)\right) = 0.095$ positions, hence a driver must be paid an additional $10.5 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 improved the average rank finish at the end of the race, but only by a small amount and with diminishing returns.[26] A driver who did not finish a race due to a driving error (crash) averaged a 9.146 worsening in rank finish, slightly higher than the team DNF value.

VI. The decomposition of total variation

The computation of the shares of total variation attributed to the driver, team, interaction between driver and team, and random component is straightforward to compute for the 2012–19 sample period. Following step 1, the total sum of squares in rank finishes is 128,080. In step 2, the regression of the team panel model yielded an R^2 equal to 0.5563. The residuals from this regression were then regressed on the driver panel model in step 3, yielding an *SSR* equal to 18,251. Dividing this number by the total sum of squares, 128,080, in the rank finish variable yields an R^2 equal to 0.1425. The driver specific model explained just 14.25% of the total variation in rank finishes. In step 4, the R^2 for the driver specific model from Table 6 is 0.5051, resulting in a share due to the interaction of driver and team equal to $0.5051 - 0.1425 = 0.3626$ or 36.36%. Finally in step 5, the share of total variation in rank finishes due to the team specific model is equal to $0.7024 - 0.3636 - 0.1425 = 0.1963$ or 19.63%. The random component accounts for 29.76% of the total variation in rank finishes.

The four-step procedure outlined in task one above was repeated for each of the 2012–19 F1 seasons individually. Table 7 reports these estimates based on the fixed effects FGLS regression results for the team and driver regression models.[27] The results suggest that the skill of the drivers contributes the least to explaining the rank finishes,

[25]Although we speak in terms of an increase in salary, we interpret it to reflect the driver's expected marginal product.

[26]The estimated coefficients for *racestarts* and *racestarts*^{2} suggest that a driver does not reach a maximum effect for race experience until approximately 75 prior races. After that point, further racing experience *reduces* the average rank finish.

[27]The coefficient estimates and summary tests for each of the F1 seasons is available in a working paper version upon request.

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 34.99% (2012). These are random factors, outside of retirements due to crashes and mechanical issues, that affect the final order of finish.[28]

VII. 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 engines (power units) that utilized two electric motors in addition to their smaller 1.6 litre V-6 gasoline engines.[29] 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 7 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 totalled 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

Table 7. Variation in rank finishes explained by driver, team, interaction and unexplained. 2012–2019 F1 seasons.

Season	Sample size	SST	R^2(step 1)	R^2_D	R^2_{TD}	R^2_T	$1 - R^2_D - R^2_{TD} - R^2_T$
2019	420	13,965	0.5719	0.1264	0.3956	0.1763	0.3017
2018	420	13,965	0.6109	0.1677	0.3260	0.2849	0.2214
2017	400	13,300	0.5160	0.2007	0.2855	0.2305	0.2833
2016	462	18,595	0.6000	0.1206	0.4097	0.1903	0.2794
2015	380	12,887	0.6196	0.0988	0.4228	0.1968	0.2816
2014	352	14,193	0.6210	0.1152	0.3948	0.2262	0.2638
2013	418	16,954	0.6240	0.1021	0.4755	0.1485	0.2739
2012	480	22,964	0.4831	0.1670	0.2841	0.1990	0.3499

[28]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 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.

[29]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.

increased to 22.62%. These percentages are significantly different from their 2012 values based on the method in Olkin and Finn (1995).[30] As lesser teams adapted to the new rules in 2015, the driver share of variation dropped further to a low of 9.88%,[31] while the interaction plus team shares increased to 62.1%.[32]

Regardless of the rule changes, the driver share of the total variation in rank finishes is consistently the smallest share in Table 7. The interaction between driver and team consistently accounts for the largest share of variation, excepting the 2012 season in which the unexplained share is the largest. By itself, this shared variation between driver salary and team budget (not including driver salaries) does not imply these are complementary 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 complementary 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 labour 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.

VIII. 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 driver cars, but also provide valuable input into car development and testing. Our results broadly agree with Bell et al (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 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

[30] 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/.

[31] Significantly different from the 2012 value at 95% confidence.

[32] Significantly different from the 2012 value at 95% confidence.

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).

Disclosure statement

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References

Aversa, P., P. Santi, and S. Haefliger. 2015. "Business Model Configurations and Performance: A Qualitative Comparative Analysis in Formula One Racing: 2005-2013." *Industrial and Corporate Change* 24 (3): 655–676. doi:10.1093/icc/dtv012.

Barzel, Y. 1972. "The Rate of Technical Progress: The 'Indianapolis 500'." *Journal of Economic Theory* 4 (1): 72–81.

Bell, A., J. Smith, C. Sabel, and K. Jones. 2016. "Formula for Success: Multilevel Modelling of Formula One Driver and Constructor Performance, 1950–2014." *Journal of Quantitative Analysis in Sports* 12 (2): 99–112. doi:10.1515/jqas-2015-0050.

Boll, R. 2020. "How to Win in Formula One: Is It the Driver or the Car?." *The Correspondent*. Accessed 30 June 2021. https://thecorrespondent.com/642/how-to-win-in-formula-one-is-it-the-driver-or-the-car/84931340736-b6c94330

Budzinski, O., and A. Muller-Kock. 2018. "Is the Revenue Allocation Scheme of Formula One Motor Racing a Case for European Competition Policy?" *Contemporary Economic Policy* 36 (1): 215–233. doi:10.1111/coep.12247.

Davidson, R. 2009. "Reliable Inference for the Gini Index." *Journal of Econometrics* 150 (1): 30–40. doi:10.1016/j.jeconom.2008.11.004.

Eichenberger, R., and D. Stadelmann. 2009. "Who is the Best Formula One Driver? an Economic Approach to Evaluating Talent." *Economic Analysis and Policy* 30 (3): 389–406. doi:10.1016/S0313-5926(09)50035-5.

Judde, C., R. Booth, and R. Brooks. 2013. "Second Place is First of the Losers: An Analysis of Competitive Balance in Formula One." *Journal of Sports Economics* 14 (4): 411–439. doi:10.1177/1527002513496009.

Lazear, E., and S. Rosen. 1981. "Rank-Order Tournaments as Optimum Labor Contracts." *The Journal of Political Economy* 89 (5): 841–864. doi:10.1086/261010.

Mantel, S., G. Rosseger, and S. Mantel. 1995. "Managing Technology at the Indianapolis 500." *Technological Forecasting and Social Change* 48 (1): 59–76. doi:10.1016/0040-1625(94)00033-S.

Marino, A., P. Aversa, L. Mesquita, and J. Anand. 2015. "Driving Performance via Exploration in Changing Environments: Evidence from Formula One Racing." *Organization Science* 26 (4): 1079–1100. doi:10.1287/orsc.2015.0984.

Mastromarco, C., and M. Runkel. 2009. "Rule Changes and Competitive Balance in Formula One Motor Racing." *Applied Economics* 41 (22–24): 3003–3014. doi:10.1080/00036840701349182.

Nalebuff, B., and J. Stiglitz. 1983. "Prizes and Incentives: An Economic Approach to Influence Activities in Organizations." *Bell Journal of Economics* 14 (1): 21–43. doi:10.2307/3003535.

Olkin, I., and J. Finn. 1995. "Correlations Redux." *Psychology Bulletin* 118 (1): 155–164. doi:10.1037/0033-2909.118.1.155.

Pesaran, M. 2021. "General Diagnostic Tests for Cross-Sectional Dependence in Panels." *Empirical Economics* 60 (1): 13–50. doi:10.1007/s00181-020-01875-7.

Phillips, A. 2014. "Uncovering Formula One Driver Performances from 1950 to 2013 by Adjusting for Team and Competition Effects." *Journal of Quantitative Analysis in Sports* 10 (2): 261–278.

Sarafidis, V., and T. Wansbeek. 2012. "Cross-Sectional Dependence in Panel Data Analysis." *Econometric Reviews* 31 (5): 483–531.

Schreyer, D., and B. Torgler. 2018. "On the Role of Race Outcome Uncertainty in the TV Demand for Formula One Grands Prix." *Journal of Sports Economics* 19 (2): 211–229. doi:10.1177/1527002515626223.

Sylt, C. 2015. "European Commission Brushes off Formula 1 Antitrust Allegations." *Forbes Magazine*. Accessed 19 May 2022. https://www.forbes.com/sites/csylt/2015/01/06/european-commission-brushes-off-f1-antitrust-allegations/?sh=79d96e1c6b5a

Wesselbaum, D., and P. Owen. 2021. "The Value of Pole Position in Formula One History." *Australian Economic Review* 54 (1): 164–173. doi:10.1111/1467-8462.12401.

APPENDIX

Data sources:

Variable	Definition	Source
rankfinish	Race position at end of race	https://www.f1-fansite.com/f1-results
teamexp	Total team expenditures excluding driver salaries	https://www.spotrac.com/formula1
salary	Driver salary in real US Dollars	https://www.spotrac.com/formula1
poll	Poll position for each driver at start of race	https://www.f1-fansite.com/f1-results
devpittime	Deviation of fastest pit stop time for team from the F1 season average fastest pit stop time for all teams	https://www.motorlat.com/and author's calculations
racestarts	Number of F1 races started prior to the current race	https://www.f1-fansite.com/f1-results and author's calculations
teamdnf	*teamdnf* = 1 if car did not finish race due to team fault	https://www.f1-fansite.com/f1-results
driverdnf	*driverdnf* = 1 if car did not finish race due to driver fault	https://www.f1-fansite.com/f1-results