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Impact of Budget, Drivers and Team Personnel on Team Performance: Evidence from Formula 1 Motorsport Industry

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Abstract

This paper investigates the importance of budget, driver and team effect on team performance of a team in the Formula 1 Motorsport competition. The research quantifies the correlation of budget and performance by analysing driver and team fixed effects, and the degree to which human capital can influence the performance of the constructors. This empirical research is conducted through the 'Felsdvreg' programme in STATA, using F1 data for 25 constructors and 110 drivers over a 20-year period (2000 to 2019). Results reveal that the quality of fixed effects is high as the driver transfer network is well-connected. Majority of the drivers switch teams at least twice, allowing the programme to generate an accurate representation of the fixed effects. Multiple models are created with different combinations of driver and team fixed effects. All models suggest that an increase in budget causes a significant increase in points scored by a constructor per season. However, this level of increase varies per model based on the combination of the added driver and team fixed effects. Furthermore, the programme generated driver and team effects are compared with real-world average performance measures. It is found that successful drivers like Lewis Hamilton and Michael Schumacher indeed show high positive driver effects and all 5 constructors who have won a championship in the last 20 years display positive team effects. The paper concludes with discussing some limitations of the data and methodology used in the analysis, followed by suggestions to improve this research for future scholars.

Keywords: Formula 1, budget, driver, constructor, performance, fixed effects.

Table of Contents

List of Tables

List of Abbreviations

F1: Formula 1 Motorsport

FOM: Formula One Management

FIA: Fédération Internationale De L'Automobile; governing body of F1 that's looks after all the rules and regulations concerning the sport.

DSQs: Disqualifications; Number of race disqualifications for a driver and team per season

DNFs: Did Not Finish; Number of races a driver/team started but did not finish as a result of incidents like accidents or a mechanical error with the car.

R&D: Research and Development

LST: Long Standing Team; a bonus given to Scuderia Ferrari for their presence in F1 since 1950s.

CCB: Constructor's Championship Bonus; a bonus given to the constructor that have scored the highest race wins in the previous four seasons of F1

DCB: Double Championship Bonus; a bonus given to the constructor that consecutively wins the constructor's world championship at least twice.

NASCAR: National Association for Stock Car Auto Racing; An American motorsport competition

1. Introduction

The Formula 1 Motorsport (from now on ‘F1’) is one of the most widely watched sporting competitions in the world with a record high TV audience of 1.92 billion in 2019 (Formula 1, 2020). Having first began in 1950, the sport is now televised and conducted globally with races taking place in more than 20 countries every year (Gutiérrez and Lozanzo, 2012). Although the primary audience for F1 is European (Italy, Spain, Germany, France, United Kingdom and the Netherlands), according to market data monitored by Nielsen, F1 fan base has recently grown significantly to other parts of the world like China, Brazil, Mexico, USA and India (Formula 1, 2020). Compared to other car racing events such as NASCAR and IndyCar, F1 is considered to be the pinnacle of innovation in the automotive industry due to its level of sophistication of technology, geographical location, diversity of circuits, drivers, teams and the building of their cars (Gutiérrez and Lozanzo, 2012). Currently, 10 teams (officially known as constructors) participate in the competition spanning over a period of approximately nine months per calendar season. Constructors are formally defined as companies that “integrate the various components and knowledge domains to assemble the final motorsport vehicle” (Motorsport Research Associates, 2003). Each constructor develops and builds two cars and races both these cars in 21 races (officially known as ‘grand prix’). The teams strive to score maximum number of points based on their finishing position in a race, to stand in contention of two titles, namely, the driver’s championship and constructor’s championship (with the latter being more important to the team and former more important to the drivers). In order to ensure a fair and safe competition, the Fédération Internationale De L’Automobile (FIA) is in charge of establishing and executing sporting regulations for F1 (Fédération Internationale De L’Automobile, 2020).

The central source of revenue for a constructor comes from sponsorships (Solitander and Solitdander, 2010). However, secondary sources such as merchandising and revenue distribution at the end of the season by Formula One Management (FOM) are also considerable sources of revenue for a constructor (Verlin, 2018). To develop and build their cars, constructors inevitably require large monetary investment per year and also need to plan their budgets for upcoming seasons. A constructor is required to build its own chassis and the body of the car, but other parts such as the power unit or gearbox can be sourced from a supplier (Castellucci and Ertug, 2010). Constructors like Ferrari, Mercedes and Renault design and manufacture their own engines and build their own cars as well. Other constructors like Red Bull Racing and Haas F1 team buy their engines from Honda and Ferrari, respectively. Unavoidably, outsourcing parts can form a large part of a constructor’s budget, although it definitely saves them immense research and development (R&D) costs. Some constructors like Ferrari, McLaren and Williams have a high pedigree and heritage in the sport (Verlin, 2018). Consequently, with an extremely successful consumer market for automobiles, firms like Ferrari, Mercedes, McLaren and Renault are likely to have a high degree of learning experience in addition to a larger financial backing to their motorsport division when compared to other constructors. As a result, the budget of each constructor can vary significantly from each other. This can have extreme consequences in the ability of a constructor to invest in R&D for upgrades, build new components when old ones wear out, design and fit new performance packages or hire skilful professionals and staff. Following this argument, it is evident that budget differences of constructors can result in differences in technological prowess, resulting in relatively richer constructors gaining competitive advantage over low-funded ones. This competitive advantage can mean that some constructors consistently perform better than others, and directly impact team performance over all the races in a season.

Waern (2018) highlights that FOM's budget distribution has created severe differences between constructors' capability to invest equal sums of money for the development of their cars. Reports from Parkes (2015) confirm that small constructors like Force India and Sauber have filed complaints in past appealing to improve the governance of the sport. This, along with Gutiérrez and Lozanzo's (2012) claim regarding the importance of efficiency in F1, forms the motivating factor to answer the research question posed below. In order to increase the competition between constructors, the FIA has brought in multiple reforms (throughout the history of F1) that address this unequal budget distribution. Although the past regulation changes were less effective in fulfilling their aims, the new budget cap of 2022 (set at approximately 175 million USD) must be adhered by all constructors, and covers major costs of designing, building, repairing and upgrading of all the components of their cars. This means that big constructors like Ferrari, Mercedes and Red Bull Racing will be forced to cut down on their driver salaries, team personnel expenses and R&D costs, making it a more level field between the constructors (Stuart, 2019). The idea that a budget gap can highly influence a constructor's team operation prompts the question of whether such budget reforms are likely to help achieve the FIA's goal of competitiveness, or if driver and team fixed effects are much better indicators of team performance? Hence, this paper focusses on the following research question:

What is the relative importance of drivers, teams and budgets in determining the performance of a formula 1 team in the constructor's championship title?

The following section of this paper presents current relevant literature in F1 and a detailed overview of the budget split of FOM. It also connects the economic theory of production function with the assumption that teams with more budget perform better on average than teams with low budget. Subsequently, the paper describes the sources of data and its treatment, and the methodology employed to obtain the results. Next, the data collected is analysed in STATA through a fixed effects framework and the results presented show a positive correlation of budget, driver and team effects on team performance. Lastly, the paper discusses the limitations of the research conducted and presents suggestions for future research.

2. Theoretical Background

2.1. Literature Review

Formula 1 has recently been a popular industry for researches in the field of economics and business, due to complex, fast paced nature of the sport and high levels of data available for analysis. As a result, several prior studies have been conducted in F1. Hoisl et al. (2014) emphasise on the role of competitive advantage gained by F1 teams as a consequence of knowledge diversity. Their empirical findings conclude that there is a positive relationship between knowledge diversity and performance, suggesting that F1 teams with a typical knowledge configuration and knowledge overlap are able to generate innovative ideas and concepts that enhances their performance. Smith (2012) examines how outside investors are able to benefit more than incumbent firms from technological discontinuities in F1. The conclusion is that radical innovation is competence destroying and social capital plays a significant role in product development with new technologies. Hence, there are weak informal social ties in F1, and outsiders benefit from new technology transfers as opposed to present incumbent investors. Jenkins and Floyd (2001) explore the evolution of technological designs in F1 to understand its dominance and contribution to survival of F1 teams. They find that F1 has high technological transparency so it is difficult to hide and patent innovation from competitors. For such industries, technological designs tend to co-evolve across firms allowing competitors to copy ideas and manufacture their own version of it, consequently increasing the industry dominance. Castelluci et al. (2011) explore the impact of ageing on productivity of F1 drivers. They find that the impact of ageing and performance of F1 drivers can be summarised as an inverse U-shaped relationship. As young drivers grow older, they gain experience and display peak performance at an age of 30-32. However, as they grow older, their performance tapers down due to slow reflexes and more fatigue. Solitander and Solitander (2010) point out that the major source of revenue for an F1 constructor is sponsorship. Other ways of generating revenue include merchandising, advertisements and the sales of consumer cars.

Waern (2018) presents the impact of unequal prize money distribution of FOM on the performance of F1 teams. Results show a strong correlation between the prize money pay-outs and the team championship position. Hence, constructors who receive high monetary pay-outs are likely to perform better. Verlin (2018) provides a detailed overview of the budget split of FOM from the 2017 F1 season.

The budget split of FOM that season distributed the base prize money evenly amongst all the constructors. Furthermore, every constructor was given a performance bonus based on their rank in the championship. However, there are three other special categories that result in some teams receiving additional bonuses. Ferrari is currently the only constructor to receive 90 million USD for being the Long Standing Team (LST), due to their presence in the sport since 1950. Additionally, the Constructor Champion's Bonus (CCB) is given to teams that have scored the most race wins in previous four seasons. This bonus has been either received by Ferrari, Mercedes, and Red Bull – teams with the highest average invested budget per season. A constructor (in this case Mercedes) also receives a Double Championship Bonus (DCB) of 30 million USD if they win the constructor's championship two or more times, consecutively. None of the other constructors receive any bonus with the exception being McLaren and Williams – who receive 30 million and 10 million USD respectively, as a heritage bonus. Under the new budget split of 2022 however, the CCB, DCB and the heritage bonus will be removed. Nevertheless, Ferrari is expected to receive the LST bonus, although the amount will be reduced.

Overall, the current articles presented above serves as a concrete basis to explore the impact of driver, team and budget fixed effects on the performance of F1 teams. While Castelluci et al. (2011) explore the impact of ageing on productivity, their explanation lacks insight on how important the driver and team effects are on the performance of F1 teams. This thesis aims to fill this gap by focussing on measuring the driver and team fixed effects. Similarly, Waern (2018) explores the impact of unequal FOM prize money distribution on the performance of F1 teams. However, Waern (2018) does not take into account other sources of revenue that can also impact the total budget a constructor spends in a season. In order to address this limitation, this paper presents a wholistic picture of the budget, taking into account the overall budget of investors to find its impact on team performance. Furthermore, in light of the new budget split of 2022, which will likely reduce the financial gap between constructors, it becomes essential to evaluate budget, driver and team effects on the performance of the F1 constructors.

2.2. Production Function

The logistics of F1 mentioned in the introduction section highlight the key factors of production employed in the production of the cars ultimately leading to better performance of the cars. Abramovitz (1956) and later Solow's (1957) discovery of technical change in the aggregate production function suggests that if Q is the output produced by a firm or an individual, then K and L represent the units of capital and labour respectively, needed to produce the Q units of output. In the case of F1 constructors, performance of the teams can be seen as the output they generate and the factors of production needed to do so are in the form of performance inputs from the car (K) and human capital (L). However, with the constant development of technology (t) and improvements in the level and quality of education, marginal productivity of these factors of production changes causes a shift in the production function. Solow (1957) uses the term "technical change" to describe these shifts and proposes the aggregate production function as Q = F (K, L; t).

In regards to F1, "technical change" is the driver of the functioning of the sport. The co-evolution of technology and competition in F1 is due to sponsorship and business changes. An example of such a co-evolution is the use of new technology (movement towards turbo-hybrid engines) and major advancements in aerodynamics and manufacturing processes (Jenkins and Floyd, 2001). Consequently, since the 1970s, the level of expenditures per team has grown significantly as sponsorship money has increased, and more mainstream automobile manufacturers support F1 (Papachristos, 2014). Everdingen et al. (2019) suggest that mainstream manufactures like Mercedes or Ferrari have additional pressure to outperform privately owned F1 constructors for brand image reasons, causing some of them to spend at times twice the amount of money per year relative to privately owned constructors. As a result, the primary areas of budget spending for F1 constructors is in new technology (t) for the development of their cars (K) along with drivers and personnel (L) to manage the business operations.

2.3. Technology

Other prime areas of expenditure for F1 constructors like Ferrari and Renault (especially in the 21st century) has been in the development and manufacturing of their own components. Not every F1 constructor however builds all the components of their car. Constructors like Force India (now Racing Point), Haas, Sauber Alfa Romeo and few others outsource major components like the engine, gearbox, etc. They can do this either from the constructors they are competing against (Ferrari, Mercedes, Renault), or a third party constructor (Honda) who does not compete in F1 at all. Although the specific regulations for outsourcing and producing inhouse can vary per season, it is evident that R&D spending differs between constructors. An analysis by Formula Money (n.d.) reveals that approximately 25% of a constructor's budget can be utilised on R&D spending, comprising mainly of facilities like wind tunnel and track testing. Everdingen et al. (2019) find that F1 constructors who have such facilities have a relatively high R&D spending compared to those who do not and as a result they rely on outsourcing components. They also conclude that constructors who spend heavily on R&D, cut back their spending on other branding activities such as advertisement and social events. Furthermore, their findings reveal that although branding activities yield positive returns on investment, constructors that invest heavily in R&D are likely to perform better compared to competitors that invest less.

2.4. Human Capital

The existing literature shows that human capital employed at various levels of managerial hierarchy (including CEO/CFO and lower level managers like operational/branch managers) can impact the performance of a firm (Mackey, 2008; Hambrick , 2007; Bertrand and Schoar, 2003; Lazaer et al., 2005). Additionally, the literature focusses on some specific attributes of managers and leaders such as their education level (Chevalier and Ellison, 1999; Mair, 2005; Goldfarb and Xiao, 2011; Juravich et al., 2017), years of experience (Goodall et al., 2011; Goodall and Pogrebna, 2015), the recognition of their work (Falato et al., 2015), other characteristics about their nature (Malmendier et al., 2011; Kaplan et al., 2012) and even joint impact of managers on performance (Peeters et al., 2015). As described by Ployhart and Moliterno (2011), managerial skills, abilities and experiences are considered as human capital. For the purpose of this paper, human capital is all the knowledge brought in by the team principles, engineers and drivers of an F1 team for the development of their cars. Hoisl et al. (2014) highlight the view that knowledge diversity and knowledge overlap are integral characteristics of F1 teams, and are highly influenced by their team principles when structuring and putting a team together. Evident from the analysis by Formula Money (n.d.), approximately 25% of a constructor's budget is spent on team, driver and director salaries. Hence, human capital forms the basis of innovation and functioning of the team. Highly innovative and efficient firms can save their time and money, and gain competitive advantage over their competitors and perform better. Specifically, F1 teams rely heavily on engineers for building the cars, on team principles for strategy and decision making, on drivers for performing on the track and during practice sessions, and the pit crew who build/repair the cars during the entire season.

Since technology and human capital play a significant role in the performance of a F1 team, coupled with the fact that investments in R&D and skilled staff requires high budget investments, analysing the impact of these investments can help answer the research question. The following section presents the data used for the empirical research and the methodology for fixed effects analysis.

3. Data and Methodology

3.1. Data: Sources and Treatment

To analyse the impact of budget on the performance of F1 teams, a panel dataset was constructed using numerous performance indicators for F1 drivers and constructors. The data collected covers a 20-year period (2000-2019) with all driver and constructor data being gathered from the official FIA website. This data includes performance indicator for every driver per season such as points scored, podiums attained, number of pole positions during race qualifications, total race wins, number of fastest laps, number of races the driver did not fully finish (DNFs) and number of disqualifications (DSQs). On the constructor side, the performance indicators collected remain the same as that for drivers (points, podiums, pole positions, wins, fastest laps, DNFs). For constructor's budget data, numerous sources were used such as journal articles (Judde et al., 2013; Schot, 2002), reports (Wood, 2008; France-Presse, 2019), news articles like CNN (Scanlon, n.d.) recognised motorsport magazines like Racefans (Collantine, 2008; Rencken, 2019, 2020), Autosport (Rencken, 2013, 2014, 2015, 2016, 2017), and motorsport forums like Autosport (Formula 1 teams' budgets [Kubiccia], 2011), F1technical (F1 budgets 2011: Who does more for less? [bot6], 2011), and Team Liquid (Formula 1 – 2012 [Zere], 2012).

The data collected was tailored to needs of the analysis and a few changes were needed to arrive to the final dataset. One essential change that requires mentioning is that, upon initial collection of the data, 28 different constructors were identified over the 20-year period. However, F1 team sponsorships can change frequently, without necessarily altering the management of the team. Hence, constructors undergo a change in their team name without actually making any changes to their human capital or manufacturing facilities. Such constructors were clubbed together and considered as one team. To give an example, Virgin Racing entered F1 in 2010, and over the 7 years of its participation in the competition, their team name changed 5 times. To simplify identification of such constructors, Virgin Racing is written as Marussia Virgin (based on the most commonly used name) and is considered as a single constructor despite its name changes. Another reason for doing this is that if such constructors are not clubbed into one, driver transfers will be exaggerated and the true driver or team effect on performance will be either overstated or understated. In the end, approximately 500 observations were recorded for a total of 25 constructors and 110 drivers during the 20-year period.

3.2. Methodology

To explore the effect of budget on team performance, the empirical analysis presented in this paper analyses the driver, team and budget fixed effect on performance of the team. As explained in the theoretical background section, the aggregate production function comprises of technology (t), car performance (K) and human capital (L) to determine the units of output (performance) produced. As mentioned earlier, approximately half of a team's budget is spent on R&D and personnel salaries (Formula Money, n.d.). Hence, it is safe to assume that R&D (t), car performance (K) and drivers/team personnel (L) have a large effect on the performance of the team.

Historically, two-way linear fixed effects regression has been commonly applied in econometric analysis, as this methodology allows researchers to incorporate time-invariant individual characteristics. As these effects are implicitly captured by taking within-individual differences over time, there is no need to include time-invariant characteristics (van Kippersluis, 2020). Although time-varying characteristics like education of driver can be included in the analysis, they are unlikely to significantly impact the results. This is because drivers are not expected to gain additional years of education alongside driving. The analysis conducted in this paper is done using STATA's add-on command "FELSDVREG" and estimations of driver and team fixed effects are obtained. Similar to the analysis of driver and team fixed effects in this paper, in the fixed effects framework, researches can include a minimum of two fixed effects and measure (for instance) the impact of student and teacher effects (Cornelissen, 2008). The following equation shows the empirical estimate for the fixed effects regression conducted in this paper:

$$Y_{sji} = \beta X_{sj} + \delta_i + \gamma_j + \varepsilon_{sji}$$

where Y is the dependent variables and denotes the change in a constructor's relative points in percentage terms; s refers to the season (year) of the F1 competition; j denotes the constructor name (or id number) given to each of the 25 constructors in the dataset; i symbolises the driver name (or id number) given to each of the 110 drivers in the dataset; β represents the coefficient of a constructor's relative budget; X is the independent variable that denotes a constructor's relative budget; δ denotes the driver fixed effect; γ refers to the team fixed effect and ε denotes the error term. All models presented in table 5 (see results section) use different versions of this equation to estimate the impact of budget, driver and team fixed effects on the points scored by a constructor in a given season. Model 1 excludes both driver and team fixed effects whereas the rest of the models include either team (model 2) or driver (model 3) fixed effect, or both (model 4). Model 5 on the other hand takes the independent variable (budget) as a constant but includes both the fixed effects.

To measure the driver fixed effect, it is essential that drivers can be observed moving between different constructors. For example, Ferrari employed Michael Schumacher and Rubens Barrichello as their two drivers for the 2000 season. If Ferrari stayed with these drivers for the 20-year period, it would not be possible to identify the impact of drivers in Ferrari's performance. Since F1 drivers are transferred between teams on a frequent basis, the probability that an F1 team has employed multiple drivers over many years is high. Hence, fixed effects are a suitable method of measuring the impact of budget on a team's performance.

4. Results

4.1. Summary Statistics

Table 1 shows summary statistics of the variables used in the two-way fixed effects regression analysis. To briefly run through the variables, 'constructorid' and 'driverid' are numbers given to identify every constructor (team) and driver in order to track their movement from one team to another. Variables with 'd_' as the prefix, represents data for drivers, while 'c_' represents data for constructors over the 20-year period.

Table 1: Summary statistics of variables used in data analysis

Variables	Mean	Standard Deviation	Minimum value	Maximum value
constructorid	-	-	1	25
driverid	-	-	1	110
year	-	-	2000	2019
d_points	53.12	83.65	0	413
d_podiums	2.26	4.13	0	17
d_polepositions	0.75	2.08	0	15
d_wins	0.75	2.06	0	13
d_fastestlaps	0.75	1.68	0	10
d_DNFs	3.90	2.65	0	12
d_DSQs	0.02	0.14	0	1
c_budget	221.42	127.67	32.25	611.60
c_avgbudget	225.43	41.71	133.10	281.50
c_relbudget*	0.98	0.53	0.15	2.41
c_points	113.25	163.01	0	765
c_avgpoints	113.37	63.70	30.9	217.4
c_relpoints*	0.99	1.22	0	5.79
c_podiums	1.58	3.53	0	19
c_polepositions	4.83	7.85	0	33
c_wins	1.58	3.64	0	20
c_fastestlaps	1.63	3.09	0	14
c_DNFs	9.19	4.56	1	23

Observations for all variables = 494
c_relbudget* = ratio of c_budget and c_avgbudget for every constructor per year
c_relpoints* = ratio of c_points and c_avgpoints for every constructor per year
c_budget and c_avgbudget show budget data in millions of USD

The points system in F1 has changed multiple times. To briefly explain this, in the period 2000 to 2009, a maximum of 10 points were awarded to the driver winning a race. Until 2002, only the top 6 drivers received these points. However, post 2002, the points spread was amongst top 8 drivers in order to incentivise mid-field teams to perform better and make the competition closer and more interesting. From 2010 onwards, the points system was revamped with the race winner now winning 25 points with all top 10 drivers scoring some points. The points gap between drivers increased further as in 2014, double points were awarded to the top 10 drivers, meaning that instead of receiving 25 points for a race win in 2013, the race winner instead received 50 in 2014. This change created a large gap disadvantage for non-competitive teams and the points structure reverted back to the one adopted in 2010. Lastly, in 2019, the driver with the fastest lap of the race was awarded 1 point irrespective of his finishing position (Mitchell, 2018). Since the points structure has changed multiple times, it is difficult to compare team performance over the 20-year period on the basis of the absolute points scored by a team per season. Hence, relative points are computed by calculating the average points scored per season and taking the ratio of the actual points scored by a team with the average of the season. This approach does not alter the standard deviation of points scored between teams, but it allows to compare different seasons to one another by removing the effect of points structure from the analysis. This data is stored in the variable 'c_relpoints'. It can be seen from table 1 that the maximum value for relative budget is 5.8 times the average points in a season, suggesting that some teams have displayed dominant performances in F1.

A similar modification is done to the constructor's budget. This is because (despite the FIA introducing frequent budget caps), the average budget spent per season has constantly increased from 2000 to 2019. While USD 200 million can be classified as one of the highest budgets invested by an F1 team in 2000, such a figure is considered only average for 2019. Although, part of this difference can be attributed to inflation (Duxbury, 2020), another reason for the increase can be the rapid developments in automobile technology and increased sponsorship money. Hence, to account for these reasons, average of the total budget per season is calculated. Thereafter, every constructor's budget in the same season is compared to the average budget of the season and taken as a ratio of the actual budget to average budget. This data is stored in the variable 'c_relbudget'. It is evident from minimum and maximum values for the budget variables, that some constructors have spent almost 2.5 times the average budget in a season, making the spread of the budget extremely uneven.

4.2. Analysis of driver network and quality of fixed effects

Before delving deeper into the results of the analysis, it is essential to identify how well connected is the network of drivers. Table 2 summarises in how many teams have the drivers been employed in. It is observed that 42 out of the 110 drivers are only seen driving for 1 team throughout their career. These drivers can be termed as 'stayers', meaning that they do not switch teams. Hence, they finish their career under 1 constructor. Similarly, 68 drivers are seen to be employed in at least two different teams (see Appendix I for detailed overview of the different number of teams the drivers in the data sample have driven for). Since 'movers' are drivers that switch teams at least once, it is evident from table 2 that majority of them drive for a minimum of two different constructors. This is a positive observation for the fixed effects analysis as a well-connected network of driver movements will explain the driver and team effect better, as opposed to no or less driver transfers. Such a network of transfers means that driver effect on performance in different teams can be analysed and the results can be considered as reliable relative to a poorly connected network.

Table 2: Number of movers

Mover	Frequency	Percent	Cumulative Frequency
0 = stayer	42	38.18	38.18
1 = mover	68	61.82	100.00
Total	110	100.00	

In order to confirm the quality of the network of driver transfers, table 3 presents the distribution of the number of drivers that have moved or switched teams. This table can be used to determine the quality of the team fixed effects with the idea that high number of movers determines high quality of fixed effects estimation and low movement indicates a low quality (Cornelissen, 2008). As the table shows, there are no constructors that display 0 movement of drivers and all the 25 firms have less than 20 movers. Since driver movement is an integral aspect of this data analysis, it is a positive sign that all teams show respectable number of driver transfers.

Table 3: Number of drivers that move between constructors

Movers per constructor	Frequency	Percentage	Cumulative Frequency
1 – 5	8	32.00	32.00
6 – 10	11	44.00	76.00
11 – 20	6	24.00	100.00
Total	110	100.00	

All the 25 constructors are now divided into groups within which there is driver mobility. As it can be seen from table 4, all drivers are part of group 1. This essentially means that none of the drivers are disregarded from the analysis with all 494 observations being observed. This is ideal as this information suggests that even smaller teams that participated temporarily for a few seasons are also well-connected with the rest of the teams. Within the group, 1 constructor effect is not identified because one effect needs to be taken as a reference in order to express the differences of all other constructors from this reference.

Table 4: Groups of constructors connected by driver mobility

Group	Drivers-years	Drivers	Movers	Constructors
1	494	110	68	25
Total	494	110	68	25

Each firm has at least 1 mover

Number of constructor effects identified: 25 – 1 = 24 [Number of constructors – Number of groups]

4.3. Fixed effects regression results

In order to compute the effect of budget on team performance, multiple models are presented below in table 5. The first model is a simple linear regression of 'c_relpoints' and 'c_relbudget' without any driver or team fixed effects. This model gives us a budget coefficient of 1.63 and can be interpreted as when budget is increased by 1%, points are expected to increase by 1.63%. Model 2 adds the team fixed effects to observe the impact team personnel have on the performance of their team. As expected, the budget coefficient drops from 1.63 in model 1 to 1.44 in model 2. This means that when controlling for team fixed effects, a 1% increase in budget results in a 1.44% increase in points. The reason for this decrease in coefficient (from model 1 to model 2) is that controlling for team fixed effects takes away part of the budget effect on the expected points scored by a team per season. Evidently, this can also be seen from the increase of R-squared value from 0.51 in model 1 to 0.66 in model 2, showing that model 2 is a better fit at explaining the budget effect on team performance. Model 3 excludes team fixed effects and instead includes the driver fixed effects. Similar to what is observed in model 2, coefficient of model 3 (1.34) is also smaller than that of model 1 (1.63). According to this model, a 1% increase in budget results in an increase of 1.34% of points scored by a team per season. The lower coefficient for model 3 relative to model 2 suggests that driver effects are larger than team effects, although the fit of the model remains similar with an R-square value of 0.67.

Model 4 includes both, driver and team fixed effects. As the results show, the coefficient of model 4 drops further to 1.32, suggesting that adding driver and team fixed effects reduces the effect of budget on points scored. Hence, according to model 4, a 1% increase in budget will increase total points for a constructor by 1.32%. By ignoring specific human capital or firm capabilities, if it is true that the better drivers are paid more (which is probably a safe assumption to make), then a correlation between the fixed effects and salaries can be expected. Since salaries are part of the budget and are allocated to the human capital of the team, the effect of salaries will therefore be overestimated. Hence, it is logical to expect the coefficient to decrease (compared to models 1, 2 and 3) by adding in the driver and team fixed effects in model 4. The decrease in coefficient observed from model 1 onwards to model 4 is in line with the expectation that more skilled/better human capital positively affects team performance. For all models, the coefficient is statistically significant at a 1% significance level.

Table 5: Regression results

Dependent Variable: c_relpoints	Model 1 (No FEs)	Model 2 (Team FE)	Model 3 (Driver FE)	Model 4 (All FEs)	Model 5 (Constant budget)
c_relbudget	1.63*** (0.08)	1.44*** (0.16)	1.34*** (0.12)	1.32*** (0.16)	-
Constant	-0.60*** (0.06)	0.22 (0.35)	0.82 (0.61)	-	2.67
Observations	494	494	494	-	-
F-test	375.95***	83.36***	130.93***	2.25***	5.81***
R-squared	0.51	0.66	0.67	-	-

*** Denotes significance at the 1% level and parenthesis denote standard error

Similar to model 4, model 5 includes team and driver fixed effects. However, for this model the 'c_relbudget' is taken as a constant for all the teams. This model does not generate a coefficient for budget but has an implication on the explanatory power of the driver and fixed effects. This is because teams spend their budget on personnel, performance of the car and in R&D to become innovative.

Therefore, including driver/personnel salaries (in model 4) can take away part of the real effect of human capital on team performance. In this regard, as we can see from table 6, the driver effect of 18% and team effect of 13.6% can really be considered the minimum estimate of the driver and team fixed effects. This is because the direct effect of salaries has been taken away from model 4. Therefore, setting budget as a constant in model 5 avoids taking away part of the driver and team fixed effect.

There are two ways of interpreting the result of model 5. On the one hand, team managers and investors can directly control how much money they spend on drivers and personnel. Teams can choose the grade of driver they want and decide to pay him more or less than his market value. In this way, part of the human capital effect on team performance is incorporated within the budget effect. On the other hand, it is not possible to create drivers with unmatched skills and talent like Michael Schumacher or Lewis Hamilton, who are proven drivers and demand a relatively large amount of money to be hired. Since the effect of such drivers can be a lot more than what salaries can explain, the true driver effect is understated. In this sense, there is a minimum and maximum interpretation of what human capital contributes to the performance of a constructor. This is because upon taking budget as a constant in model 5, some of the human capital impact is taken out since it forms part of the salary and therefore budget. However, not controlling for budget can also result in an inaccurate representation of the effect of human capital as budget incorporates potential investments in R&D that are now incorrectly attributed to human capital effects. Hence, not controlling for budget can result in the error of overstating the impact of human capital on team performance.

4.4. Variance Decomposition

Results of the minimum-maximum human capital effects can be seen from the variance decomposition produced by the 'Felsdvreg' programme in table 6. Multiple observations can be drawn from table 6. First, the effect of budget in explaining team performance is estimated to be 41.15%. This is in line with Formula Money's (n.d.) analysis that teams spend about 50% of their budget on human capital and to enhance the performance of their cars. Second, model 5 shows that driver and team effect accounts for approximately 70% in explaining the performance of F1 constructors. The residual or unexplained variance of approximately 30% are other factors such as R&D, production, manufacturing and operations of the business. Furthermore, model 4 shows the minimum effect of budget, driver and team on a constructor's performance per season, while model 5 shows the maximum effect. By controlling for budget in model 5, driver effect increases by 2.52% while the team effect increases by 33.73%. The residual effect also increases by 4.89%, suggesting that the budget effect of model 4 underestimates the true effect of R&D as well.

Table 6: Explanatory power of the model

Expected explanatory power (%)	Model 4 (All FEs)	Model 5 (Without budget FE)	Change in explanatory power of FEs
Budget effect	41.15	0	-
Driver effect	18.32	20.84	+2.52
Team effect	13.63	47.36	+33.73
Residual (unexplained variance)	26.90	31.79	+4.89
Total	100.00	100.00	

4.5. Comparison of driver and team effects with performance measures

Out of the 25 constructors, only 5 teams have won the constructor's championship in the 20-year period. Ferrari dominated in the early 2000s, winning 5 consecutive championships from 2000-2004 and later in 2008. Red Bull and Mercedes dominated post 2009 with consecutive 4 and 6 championship titles respectively. Other championship holders include Renault with 2 titles (2005 and 2006), McLaren with 1 title in 2007 and Brawn GP with 1 title in 2009.

In order to check whether driver and team effects actually make a positive impact in the sport, table 7 presents the team effects and table 8 presents the driver effect for the top 10 teams and drivers in the dataset over the period 2000 to 2019. These effects are compared with performance indicators like wins, pole positions, podiums and fastest laps. Tables 7 and 8 show an average of these performance measures for the 20-year period to account for both good and bad performance of the drivers and teams. The tables show teams and drivers who have participated in F1 for at least 5 years (during the 20-year period) to rule out those who had an extremely short successful/unsuccessful career. For example, Brawn GP participated in F1 in 2009 and won the championship that year. Although they performed extremely well, they did not participate further. Hence, due to the lack of observations to assess the impact of the team on their performance, Brawn GP's team effect has been left out from table 7.

To obtain the team and driver fixed effects, the mean effect is calculated and subtracted from the actual effect, so every effect is measured on the same scale. This is because when calculating the fixed effects, STATA takes the first driver and team as a reference and calculates the effects of others using this benchmark. For example, Ferrari has a constructor id of 1 and is therefore taken as the reference team. STATA analyses whether other teams perform better or worse than Ferrari. Since Ferrari's performance can be expected to be very high, setting this as the benchmark is not ideal when it comes to using the programme generated team effects for analysis. Therefore, the mean driver and team effects are subtracted from the actual effect as a solution to the scaling problem.

Table 7: Team effects

Constructor Name	Team Effect	Average performance measures			
		Wins	Podiums	Pole Positions	Fastest Laps
Red Bull Racing	0.59	3.85	3.79	10.76	4.12
Scuderia Ferrari	0.49	4.81	5.43	16.19	5.52
Lotus F1 Team	0.28	0.00	0.40	4.93	1.00
Force India	0.15	0.12	0.00	0.52	0.44
Renault	0.11	1.22	1.14	3.75	0.78
Mercedes Petronas AMG	0.09	10.3	9.30	19.40	6.60
McLaren	0.08	1.23	3.00	8.85	3.50
Minardi	0.02	0.00	0.00	0.00	0.00
Scuderia Toro Rosso	0.00	0.03	0.09	0.03	0.03
BMW Sauber	-0.06	1.31	0.08	0.08	0.15

Table 7 shows that Red Bull Racing and Ferrari have the highest team effects on performance with 0.59 and 0.49, respectively. This is in line with the expectations since both these constructors have won multiple constructor's world championship titles in the last two decades. Moreover, it can be seen that these constructors have relatively higher wins, podiums, pole positions and fastest laps on average per season than most of the other constructors. Although Ferrari's average performance is higher than Red Bull, this is likely because in the early 2000s Ferrari won 5 consecutive constructor's world championships while Red Bull was still not part of the sport. Nonetheless, both teams show a high team effect, as expected. Only Brawn GP has a higher team effect of 2.35 but is excluded from the table for reasons mentioned earlier. Moving down the list of constructors, it is evident from the table that as the average performance decreases, the team effect also appropriately decreases. Overall, all 5 constructors who have won a championship in the last 20 years (Red Bull, Ferrari, Mercedes, Renault and McLaren) are part of the table and show positive team effects.

One exception to note is the team effect of Mercedes Petronas AMG. Despite a low team effect rating, they indicate a higher average performance than even Red Bull and Ferrari. The low team effect is surprising because Mercedes has won the last 6 consecutive world titles and have dominated the competition in the new turbo-hybrid era of F1. There can be multiple causes for this observation. Mercedes is a relatively new entrant to the sport as they started participating in F1 only in 2010. In order to build a car and develop the team to a level it could compete against the likes of Ferrari and Red Bull, it is likely that they lacked performance in their early years of participation. Empirically, another cause for their low team effect yet high performance numbers, is the high driver effect (see table 9) of Valtteri Bottas and (in particular) Lewis Hamilton. Despite having Michael Schumacher and Nico Rosberg (both world champions) driving for them in their early years, Mercedes only started winning world championships after Valtteri Bottas and Lewis Hamilton joined their team. To check if this is the case, consider the information in table 8 on Mercedes' performance decomposition based on the period in which Lewis Hamilton and Valtteri Bottas joined the team. Table 8 reveals that once Lewis Hamilton joined the team in 2013, the team performed significantly better in all aspects. This performance is further elevated with the arrival of Valtteri Bottas with more overall points, podiums and fastest laps. Since the model suggests that Mercedes' team effects do not match the performance level they display, it must be the driver effect of Lewis Hamilton and Valtteri Bottas that significantly increases their performance. Although it may be a true or a false artefact of the way this methodology establishes driver and team fixed effects, it is difficult to deny the reality that Lewis Hamilton is one of the best drivers in F1.

Table 8: Mercedes' performance decomposition over the years

Time Period	Average performance measures				
	Points scored	Wins	Podiums	Pole Positions	Fastest Laps
Before Lewis Hamilton (2010 to 2012)	86.83	0.17	0.80	0.17	0.50
After Lewis Hamilton (2013 to 2016)	316.13	6.75	13.13	8.00	4.38
With Lewis Hamilton and Valtteri Bottas (2017 to 2019)	343.67	6.33	13.83	6.33	4.67

Table 9 shows the top 10 driver effects and indicators for their average performance. It can be seen that some of the most popular and successful drivers like Lewis Hamilton and Michael Schumacher are at the top of the list, in line with expectations. Their performance numbers also suggest that these drivers are highly skilled and talented to make an impact to the team they drive for. Data collected shows that Michael Schumacher has won 7 driver's world championship titles and Lewis Hamilton currently holds 6. Although Valtteri Bottas has not won a championship, he has consecutively scored a large number of points for Mercedes to win the constructor's championship for the team and the performance figures evidently represent this effect. Similar to team effects in table 7, the driver effects in table 8 also decrease as average performance per season of the drivers drops down the list.

Table 9: Driver effects

Driver Name	Driver Effect	Average performance measures			
		Wins	Podiums	Pole Positions	Fastest Laps
Lewis Hamilton	1.22	6.46	11.62	6.77	3.62
Valtteri Bottas	1.12	1.17	7.50	1.83	2.17
Michael Schumacher	0.77	5.60	8.40	4.50	3.80
Rubens Barrichello	0.68	0.92	5.17	1.00	1.42
Juan Pablo Montoya	0.65	1.17	5.00	2.17	2.00
Nico Rosberg	0.47	2.09	5.18	2.73	1.82
Ralf Schumacher	0.39	0.75	2.63	0.75	0.88
Sebastian Vettel	0.34	4.00	8.54	4.23	2.27
Mark Webber	0.25	0.75	3.50	1.18	1.58
Felipe Massa	0.15	0.73	2.73	1.07	1.00

However, in regard to Sebastian Vettel, it is a surprising result to see a 4-time driver's world champion 7th on the list, below drivers who have none or less championships than him. Similar to Mercedes's position, Vettel's performance is better than Valtteri Bottas, yet his driver effect is relatively low at 0.34. All of Vettel's 4 world championships came with Red Bull Racing in the years 2010 to 2013. In 2015, he moved to Ferrari and has since not won a driver's world championship. A closer look at his performance figures with Red Bull Racing (prime championship winning years of 2010 to 2013) and Ferrari (non-prime years with no championship wins of 2015 to 2019) in table 10 shows that his performance declined post his movement to Ferrari.

Table 10: Sebastian Vettel's performance comparison (prime vs non-prime years)

Constructor Name	Average performance measures				
	Points scored	Wins	Podiums	Pole Positions	Fastest Laps
Red Bull Racing	331.50	8.50	13.25	10.00	4.75
Scuderia Ferrari	273.00	2.80	10.80	2.40	2.80

The main figure to compare from table 9 is the difference in the average number of race wins per season when Vettel drove for Red Bull Racing (8.50) compared to that with Ferrari (2.80). The total number of points scored, and podium finishes are also relatively higher in his prime years with Red Bull compared to that with Ferrari. The difference in wins can be a consequence of Vettel's lack of qualifying pace as the average number of pole positions drop from 10.00 to 2.40 and fastest laps from 4.75 to 2.80. Such a difference in performance suggests that despite being a 4-time world champion, Vettel's performance dropped in recent years with Ferrari. This may explain why the Vettel's driver effect is not amongst that of the top drivers in the list. Overall, the driver effects shown in table 8 are consistent with that expected in the real-world competition.

In the next section, this paper discusses some limitations of the research and discusses some suggestions for future research. The last section summarises the main findings from this paper and concludes the study.

5. Limitations and Recommendations for Future Research

The analysis presented in the results section shows that the impact of budget on team performance is significantly positive. Specifically, model 4 shows a 1% increase in budget leads to a 1.32% increase in the points scored by a team per season. Although, the results may appear convincing, the reliability and accuracy of the research and can be questioned due to some limitations from a data standpoint. The budget data had to be obtained from multiple sources like journal articles, sports magazines and website forums. Moreover, at times there was inconsistency observed between two sources of data and the more reliable source was chosen based on subjective decision making. The fact that budget data for F1 constructors is not readily available on official records (such as financial statements) can question the reliability and accuracy of the results. However, given this limitation, the budget figures of the teams were in line with expectations as constructors like Ferrari and Mercedes are indeed found to spend significantly more money than other non-mainstream constructors like Williams. Having access to an official financial database disclosing budget figures for F1 teams may yield a different coefficient for budget, although the positive correlation between budget and points can be expected nonetheless.

Mercedes' low team effect despite their high performances indicate a limitation of the fixed effects methodology used in this paper. While tables 8 and 9 do explain that driver effect of Lewis Hamilton and Valtteri Bottas has significantly increased the performance of the team, it is difficult to assume that team principle, engineers and mechanics have no role in the team's recent success. If part of this enhanced performance is indeed a result of the team personnel, then the fixed effects methodology certainly does not capture the full effect of the budget investments Mercedes has done throughout these years. Furthermore, this methodology highlights a general downside in the sense that it assumes that teams are not allowed to change over time. Perhaps, if a more sophisticated model were to be used, it may be observed that Mercedes' team effect improves over the years to complement the increase in their performance.

Peeters et al. (2015) show that managers have unique qualities and abilities that make the management more productive if the match quality of those managers aligns well with abilities and qualities of other managers across hierarchal organisational levels. In the context of this research, by better manager match quality, strategic decisions and operations of the team can become more efficient which can improve the performance of the teams. This is a limitation of this study since match quality of managers are not included in this research and can therefore skew the team fixed effects. This is because the performance data for the team may not entirely capture the soft skills and personality traits of managers at different hierarchal positions in the team and the impact they generate on team performance. Similarly, manager-driver match quality can also be a factor that can affect the performance of the driver in a team. For instance, such a reasoning may be one of the factors (amongst many others) why Sebastian Vettel's performance declined after his switch from Red Bull Racing to Ferrari. Constructor's championship points show that both teams compete fiercely against each other and have ended their seasons with similar points. Furthermore, the team effects in table 7 also show that they are closely matched in the performance aspect too. Hence, other factors such as comfort/trust of the driver within the team principle and staff or the atmosphere of the team, may be one of the causes for Vettel's decline in performance with Ferrari. In other words, match of personality traits of team principles with other managers and drivers can play a significant role in the performance of a team. Since this paper falls short of analysing this, it is a potential research topic for future scholars.

The theoretical background section of this paper discusses the main areas of spending for an F1 constructor, namely, human capital (L) and car development (K) through innovation and technology (t). As observed from the variance decomposition presented in table 6, the residual effect (approximately 30%) can be assumed to comprise mainly of technology and R&D needed to make developments to the performance of the cars. Part of this effect is explained by the budget effect of approximately 41% (since technology investments require budget). However, to analyse the impact of technology on team performance, dataset measuring innovativeness in the form of patents and explicit role of technology is required. Due to time and resource constraints, this research lacks a more complete explanation of the role of technology fixed effects on performance, therefore leaving a gap for future researchers to explore.

6. Conclusion

The research presented above begins by first identifying the lack of empirical analysis of budget on team performance in the F1 industry. Referring to Solow's (1957) aggregate production function model, the paper presents evidence that some of the key areas of budget spending for an F1 constructor is in human capital, car manufacturing and technological development in the form of innovation. This research therefore focusses on the human capital aspect of the budget and identifies key areas of human capital employed to generate the best possible performances. These include drivers and team members such as team principle, staff and engineers.

The models presented in the analysis provide evidence that driver and team fixed effects play a significant role in determining the performance of a team. On an average, the model with driver and team effects estimates that a 1% increase in budget leads to a 1.32% increase in points. Since hiring skilled human capital requires monetary investments, this suggests that teams with the highest budgets are generally teams that also perform better than those that do not have high financial power. Furthermore, it is observed that talented drivers who win world championships indeed display positive driver effects on team performance. Additionally, teams who win world championships also show a positive team effect on performance. Hence, from a competition point of view, it is not surprising that the FIA has imposed bans and made regulation changes to introduce budget caps. The budget cap of 2022 is also expected to limit the R&D spending and bridge the financial advantage that some teams have over others. This should allow low-funded team to become more competitive, ultimately making the sport more interesting for the audience.

References

Formula 1. (2020, January 21). F1 broadcast to 1.9 billion total audience in 2019.

Gutiérrez, E., & Lozano, S. (2012). A DEA Approach to Performance-Based Budgeting of Formula One Constructors. *Journal Of Sports Economics*, *15*(2), 180-200.

Motorsport Research Associates. (2003). *A study into the UK motorsport and performance engineering cluster*. Department of Trade and Industry.

Fédération Internationale De L'Automobile. (2018, December 13). Organisation.

Solitander, M., & Solitander, N. (2010). The sharing, protection and thievery of intellectual assets. *Management Decision*, *48*(1), 37-57.

Verlin, K. (2018, April 11). How the Formula 1 prize structure works and how it will change in 2021.

Castellucci, F., & Ertug, G. (2010). What's in It for Them? Advantages of Higher-Status Partners in Exchange Relationships. *Academy Of Management Journal*, *53*(1), 149-166.

Waern, L. (2018). *A first assessment of the financial distribution by the FOM and performance in Formula 1.* Gothenburg University Publications Electronic Archive.

Parkes, I. (2015, September 29). F1 teams lodge official EU complaint over 'unfair' structure. *Autosport*.

Stuart, G. (2019, October 31). 10 ways the 2021 rules will improve F1.

Hoisl, K., Gruber, M., & Conti, A. (2014). Knowledge Diversity & Knowledge Overlap in R&D Teams: Evidence from the Formula 1 Motorsport Industry. In *Paper present at DRUID Society Conference* (pp. 16-18).

Smith, D. J. (2012). Technological discontinuities, outsiders and social capital: a case study from Formula 1. *European Journal of Innovation Management*.

Jenkins, M., & Floyd, S. (2001). Trajectories in the evolution of technology: A multi-level study of competition in Formula 1 racing. *Organization Studies*, *22*(6), 945-969.

Castellucci, F., Padula, M., & Pica, G. (2011). The age-productivity gradient: Evidence from a sample of F1 drivers. *Labour Economics*, *18*(4), 464-473.

Abramovitz, M. (1956). Resource and Output Trends in the United States Since 1870. In *Resource and Output Trends in the United States Since 1870* (pp. 1-23). National Bureau of Economic Research.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 312-320.

Papachristos, G. (2014). Technology, performance and team adaptation to regulation in Formula 1. In *32nd International Conference of the System Dynamics Society, Delft, The Netherlands, 20-24 July 2014; Authors version*.

Van Everdingen, Y., Hariharan, V. G., & Stremersch, S. (2019). Gear Manufacturers as Contestants in Sports Competitions: Breeding and Branding Returns. *Journal of Marketing*, *83*(3), 126-144.

Formula Money. (n.d.). *The economics of Formula 1* [Infographic]. Raconteur.net. Retrieved July 23, 2020, from https://www.raconteur.net/wp-content/uploads/2015/03/The-cost-of-an-F1-car1.jpg.

Mackey, A. (2008). The Effect of CEOs on Firm Performance. *Strategic Management Journal*, *29*(12), 1357-1367.

Hambrick, D. C. (2007). Upper Echelons Theory: An Update. *The Academy of Management Review*, *32*(2), 334-343.

Bertrand, M., & Schoar, A. (2003). Managing with Style: The Effect of Managers on Firm Policies. *The Quarterly Journal of Economics*, *118*(4), 1169-1208.

Lazear, E. P., Shaw, K. L., & Stanton, C. T. (2015). The Value of Bosses. *Journal of Labor Economics*, *33*(4), 823-861.

Chevalier, J., & Ellison, G. (1999). Are Some Mutual Fund Managers Better Than Others? Cross-Sectional Patterns in Behavior and Performance. *The Journal of Finance*, *54*(3), 875-899.

Mair, J. (2005). Exploring the Determinants of Unit Performance: The Role of Middle Managers in Stimulating Profit Growth. *Group & Organization Management*, *30*(3), 263-288.

Goldfarb, A., & Xiao, M. (2011). Who Thinks about the Competition? Managerial Ability and Strategic Entry in US Local Telephone Markets. *American Economic Review*, *101*(7), 3130-61.

Juravich, M., Salaga, S., & Babiak, K. (2017). Upper Echelons in Professional Sport: The Impact of NBA General Managers on Team Performance. *Journal of Sport Management*, *31*(5), 466-479.

Goodall, A. H., Kahn, L. M., & Oswald, A. J. (2011). Why do leaders matter? A study of expert knowledge in a superstar setting. *Journal of Economic Behavior & Organization*, *77*(3), 265-284.

Goodall, A. H., & Pogrebna, G. (2015). Expert leaders in a fast-moving environment. *The Leadership Quarterly*, *26*(2), 123-142.

Falato, A., Li, D., & Milbourn, T. (2015). Which Skills Matter in the Market for CEOs? Evidence from Pay for CEO Credentials. *Management Science*, *61*(12), 2845-2869.

Malmendier, U., Tate, G., & Yan, J. (2011). Overconfidence and Early-Life Experiences: The Effect of Managerial Traits on Corporate Financial Policies. *The Journal of Finance*, *66*(5), 1687-1733.

Kaplan, S. N., Klebanov, M. M., & Sorensen, M. (2012). Which CEO Characteristics and Abilities Matter?. *The Journal of Finance*, *67*(3), 973-1007.

Peeters, T., Salaga, S., & Juravich, M. (2020). Matching and Winning? The Impact of Upper and Middle Managers on Firm Performance in Major League Baseball. *Management Science*, *66*(6), 2735-2751.

Ployhart, R. E., & Moliterno, T. P. (2011). Emergence of the Human Capital Resource: A Multilevel Model. *The Academy of Management Review*, *36*(1), 127-150.

Judde, C., Booth, R., & Brooks, R. (2013). Second Place is First of the Losers: An Analysis of Competitive Balance in Formula One. *Journal of Sports Economics*, *14*(4), 411-439.

Schot, M. (2002). The F1 FAQ. *The Journal of Formula One Motorsport, 8*(19).

Wood, R. (2008, July 24). F1 info guide (Pt. 1): Money, money, money—The fuel of Formula One.

France-Presse, A. (2019, March 12). Cost of success: F1 giants are also biggest spenders. *Deccan Herald.*

Scanlon, G. (n.d.). Cash crisis forces Super Aguri out of F1. *CNN*.

Rencken, D. (2013, August 31). The true cost of Formula 1. *Autosport*.

Rencken, D. (2014, November 4). The true cost of Formula 1. *Autosport*.

Rencken, D. (2015, November 26). Revealed: How much F1 teams spend. *Autosport*.

Rencken, D. (2016, December 29). How much did Formula 1 teams spend in 2016?. *Autosport*.

Rencken, D. (2017, December 28). Revealed: What F1 teams really spent in 2017. *Autosport*.

Rencken, D. (2019, December 27). The cost of F1 2019: Team budgets analysed – part one. *Racefans*.

Rencken, D. (2020, January 2). The cost of F1 2019 part two: What the top teams spent. *Racefans*.

Collantine, K. (2008, September 22). Toyota has $445.6m F1 budget. *Racefans*.

Formula 1 teams' budgets [Kubiccia]. (2011, April 30). *Formula 1 teams' budgets* [Online forum post]. Autosport.

F1 budgets 2011: Who does more for less? [bot6]. (2011, June 24). *F1 budgets 2011: Who does more for less?* [Online forum post]. F1Technical.

Formula 1 – 2012 [Zere]. (2012, February 2). *The Teams and Drivers* [Online forum post]. TL.net.

van Kippersluis, H. (2020, January 22). Lecture 5: Individual fixed effects and panel data estimators [PowerPoint slides]. Canvas – Erasmus University Rotterdam.

Cornelissen, T. (2008). The Stata command felsdvreg to fit a linear model with two high-dimensional fixed effects. *The Stata Journal*, *8*(2), 170-189.

Mitchell, S. (2018, October 11). Formula 1 abandons idea of points system change for 2019. *Autosport*.

Duxbury, A. (2020, May 13). F1 cost cap: What is it, what does it cover and more questions answered. *Autosport*.

Appendix I

Appendix table 1 shows the number of teams the drivers are employed in. As observed from the table, approximately 38% of the drivers are seen to be driving for a single constructor. The rest of the 62% of the drivers are observed driving for at least two teams, meaning that they switch teams. This is essential for the fixed effects analysis as this shows that the driver network is well-connected and large number of driver transfers will mean that the quality of fixed effects identified from the analysis is high.

Appendix Table 1: Number of teams the drivers are employed in

Number of constructors	Frequency	Percentage	Cumulative Frequency
1	42	38.18	38.18
2	37	33.64	71.82
3	14	12.73	84.55
4	13	11.82	96.36
5	2	1.82	98.18
6	2	1.82	100.00
Total	110	100.00	

Appendix II

Appendix table 2 shows the number of observations per driver, which essentially gives a more detailed view of stayers and movers. For example, 20 times a driver was observed once, suggesting that there were 20 drivers out of a total of 110 drivers that have raced or been part of a F1 team only once. Since every driver's name usually appears not more than once in a season, this table gives an indication of how many years do the drivers (in the dataset) remain part of F1. Approximately, 63% of the drivers are observed three times, which suggests that F1 is a volatile motorsport where new drivers constantly replace older drivers and teams are also seen to enter and exit frequently (despite considerably high entry costs). Furthermore, about 47% of the drivers however stay in F1 for more than 3 years with some drivers (in the dataset) being part of F1 for even 15, 17 or 18 years. By observing drivers for such a long period and assuming that they constantly switch teams, driver effect can be estimated more accurately.

Appendix Table 2: Number of observations per driver

Observations per person	Frequency	Percentage	Cumulative Frequency
1	20	18.18	18.18
2	28	25.45	43.64
3	21	19.09	62.73
4	3	2.73	65.45
5	4	3.64	69.09
6	10	9.09	78.18
7	4	3.64	81.82
8	2	1.82	83.64
9	5	4.55	88.18
10	1	0.91	89.09
11	2	1.82	90.91
12	3	2.73	93.64
13	3	2.73	96.36
15	1	0.91	97.27
17	2	1.82	99.09
18	1	0.91	100.00
Total	110	100.00	