WMG Service Systems Research Group
Working Paper Series

Expert Leaders in a Fast-Moving Environment

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THE UNIVERSITY OF WARWICK

ISSN: 2049-4297
Issue Number: 08/13

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WMG Service Systems Research Group Working Paper Series
Issue number: 08/13
ISSN: 2049-4297
December 2013

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Acknowledgement: The authors are grateful to Paolo Aversa, Agnes Bäker, Mark Goodall, Dan Hamermesh, Andrea Isoni, Lawrence Kahn, Andrew Oswald, Axel Wendorff, colleagues at both an IZA brownbag and a Cass management seminar.

If you wish to cite this paper, please use the following reference:

Goodall A & Pogrebna G (2013) Expert Leaders in a Fast-Moving Environment. *WMG Service Systems Research Group Working Paper Series*, paper number 08/13, ISSN 2049-4297.

Expert Leaders in a Fast-Moving Environment

By Amanda Goodall and Ganna Pogrebna

Abstract

This study explores the effects of leaders in an iconic, high-technology, turbulent industry. We analyse 62 years of objective performance data from one of the world's most competitive sectors (Formula One competition). The study's findings provide strong support for an 'expert leader hypothesis'. The most successful leaders are disproportionately those who started as drivers or mechanics (not as general managers or university graduates in engineering). Moreover, within the sub-sample of former drivers, it is those who had the longest driving careers who went on to become the most effective leaders. Remarkably, the leader's former experience as a competitive driver is a better predictor of current organizational performance than the driving experience of the person who is actually driving for the team. The study's expert-leader findings are consistent with the hypothesis that longitudinal performance improves when a leader's knowledge and expertise correlate with an organization's core business activity.

Keywords: expert leaders, leadership, organizational performance, high-tech teams.

1. Introduction

A growing research literature examines the influence of leaders upon organizational performance and one notable new strand tries to understand the role of 'expert leaders'. Such work has attempted to separate CEO effects from industry or firm effects to calculate the explanatory power of leaders and their characteristics (e.g. Thomas 1988; Finkelstein & Hambrick, 1996; Waldman & Yammarino, 1999; Mumford, Scott, Gaddis, & Strange, 2002; Bertrand & Schoar, 2003; Jones and Olken 2005; Bennedsen, Perez-Gonzalez and Wolfenzon 2007; Yukl, 2008; Mackey, 2008; Goodall 2009a; Souder, Simsek & Johnson, 2012; Dezs & Ross, 2012; Nohe, Michaelis, Menges, Zhang, & Sonntag, 2013). To estimate leaders' effects in an exact way within real-world settings is known to be problematic (Antonakis, Bendahan, Jacquart, & Lalive, 2010, Blettner, Chaddad and Bettis, 2012); it is not possible, outside a laboratory, to randomly assign a leader to an organization. In this area of social science, therefore, the discovery of persuasive conclusions has to rest, at least in large part, on the availability of error-free observational data and on truly consistent replication across a wide range of settings.

The dataset in this study offers researchers a number of unusual advantages. One virtue of the setting is that it is representative of an industry type of increasing importance in the global economy, namely, one where there is extreme technological change and in which highly skilled individuals work together in a turbulent setting of ruthless world-class competition. It is possible, in this dataset, to observe every leader and the complete history of the chosen industry. The industry has the valuable feature that it provides exact and objective data on the performance of each leader's organization in each year. Therefore, the measurement error in our outcome variables should be zero. Moreover, we also have, within the dataset, the ability to link organizational success today to the leader's characteristics measured when those leaders were much younger. Finally, the dataset is longitudinal, and is rich enough that we are able to control, in later regression equations, for a range of other independent influences on organizational success.

The focus in this study is on leadership and performance in the high-technology industry of Formula One. The dataset, which we constructed partly by hand, makes it possible to identify and classify every leader in the six decades between 1950 and 2011, and, by using the unambiguous and homogeneous performance measures that are feasible in only rare settings like Formula One, we can in principle estimate the effects of different leader-types on organizational performance. Later analysis uses a range of econometric methods -- ones specifically chosen to account for unobserved heterogeneity and allow for multiple control variables -- to determine the relation between accumulated leader expertise and later Formula One team results.

The detailed purposes of the study are twofold. First, in this new setting we probe the 'expert-leader' hypothesis that leader characteristics that most closely align with the core business activity of the organization are associated, over time, with better performance. Second, in a unique check, we are able to examine the consequences of leaders for the performance of key followers; specifically, we can isolate the effect that different leaders have on the performance of their Formula One drivers. To make progress on these issues we first identify the technical background from which each leader emerged. We then test whether *the leader-characteristics measured decades earlier* that most closely align with the core business activity of the organization are associated with *better performance in the current year*. We are careful to control for a set of other influences on performance.

Why is Formula One (hereafter F1) an important industry to study? One pragmatic reason is that it is estimated to be worth annually approximately $6 billion (Sylt & Reid, 2011), with earnings coming from two main sources, sponsorship from major firms, and television revenues. F1 is also interesting intellectually because it is as much a competition for new technologies as it is for driving fast. The technological spillovers are numerous: they include anti-lock braking system (ABS), environmental technologies such as energy storage for use in cars, trains and soon airplanes, ultra-light carbon-fibre, real-time data monitoring systems, among many others. F1 constructors (e.g. Ferrari, Williams, McLaren, etc.) are medium sized companies that employ on average around 400 people. Constructors contract with numerous auto component suppliers because they are obliged to build their own race car chassis, and often also engines (Castellucci and Ertug, 2010).

A further reason to study the industry is because it is subject to a great deal of regulatory turbulence. The Fédération Internationale de l'Automobile (FIA) imposes strict conditions that change annually, on all aspects of F1 (the teams, technology, resources, track, tires, drivers, etc.). A link between regulation and innovation has been well documented (see Stewart 2010 for a review). This relationship is embodied in F1; regulation is unambiguously associated with innovation and performance (Jenkins, 2004; Jenkins, Pasternak, & West, 2007; Khanna, Kartik, Varma, & Lane. 2003; Jenkins 2010; Aversa, 2013; Marino, Aversa, Mesquita & Anand, 2013), and regulatory compliance produces a level playing field for all competing teams. Indeed, rule changes are sometimes made with the intention of curtailing the dominance of one team, for example, with Ferrari and Michael Schumacher in 2003 (Hoisl 2011).

The evidence presented later reveals a strong association between having driven competitively and leading successfully: F1 constructors headed by former racing drivers produce the best results. We also demonstrate that among the sub-sample of drivers it is those with the longest driving careers who go on to make the best leaders (titled principals). Our central finding is not merely a simple bivariate pattern. The results hold when we control for *the racing brand of the constructor team*, *the exact year of competition*, *the number of competitor cars in each race*, and *the circuits where Grand Prix take place*. On the suggestion of referees, moreover, we are also able to show that the key result goes through even *after adjustment for team income* (see Appendix 2: the necessary data on income are only publicly available for a recent subset of years). Second, when we examine the effect that different leaders have on their key workers -- for example the current F1 drivers -- we additionally find that the driving experience of the leader matters as much to performance as the F1 driving experience of the current team driver. There is little difference in performance when pairing an experienced driver-leader with either an experienced F1 driver or with a rookie driver; in contrast, a principal with no racing experience is apparently associated with bad performance no matter how much F1 racing the team driver has done.

2. Theoretical background and hypotheses

The idea of expert leaders, discussed further in this paper, arose from previous work that identified a link between the core business knowledge held by a leader and organizational performance. Core business is defined as the primary activity that is the organization's main source of success and profits. Studies that focus on the core-business knowledge and technical expertise of leaders have become more relevant because of recent evidence that major firms have moved away from hiring CEOs who might be considered experts or specialists (with technical degrees), towards instead the selection of leaders who are generalist managers (Frydman, 2007; Bertrand, 2009).

The suggestion that leaders and followers should share technical expertise has been studied within the context of creativity (e.g. Thamin & Gemmill 1974; Basadur, Runco, & Vega 2000; McAuley, Duberley & Cohen, 2000). Mumford, Scott, Gaddis, & Strange (2002) summarized such findings: they reported, first, that both technical and creative problem-solving skills are necessary when leading creative individuals; this combination informs how leaders create an appropriate work structure, and gives them credibility which enhances a leader's influence (2002, p. 712). Second, they argued that the evaluation of creative people and their ideas is best done by individuals who share their competencies. Third, leaders who share the same creative and technical perspective and motivation as their followers can communicate more clearly; finally, in relation to performance, they can better articulate the needs and goals of the organization (Mumford et al., 2002). In a study of research institutes, Andrews and Farris (1967) found that the best predictor of a researcher's creative performance was the leader's level of technical ability as compared with other factors including motivating others, maintaining group relationships, and the amount of autonomy granted to staff. These results were replicated by Barnowe (1975).

The studies summarized in Mumford et al. (2002) differ from our own. Importantly, they almost all used cross-sectional data at a single point in time (the one exception is Farris 1969 who had two points in time). Our study uses longitudinal data. We are also able to compare leader-characteristics against more objectively measured performance outcomes, and we can include a unique interaction analysis where it is possible to examine the effect of different leader-types on the performance of key followers.

The literature on Upper Echelons (UE) theory (Hambrick & Mason, 1984) and CEO origin is also related to the ideas of expert leaders. UE theory suggests that top managers make strategic choices that are reflections of their own values and cognitions. However, UE theory places greatest emphasis on the characteristics of the top management team, whereas our work isolates the leader.

Research on the origin of a CEO has identified a link between firm performance, among other outcomes, and whether the head was hired from outside the firm, or instead promoted from within, and if so, from which domain (see Kesner & Dalton, 1994; Shen & Cannella, 2002; Wiersema, 1995; Zajac, 1990; Karaevli, 2007; Zhang & Rajagopalan, 2004; Zhang & Rajagopalan, 2010). There is evidence that the number of outsider CEO hires have risen since the early 1990s (Lucier, Schuyt & Handa, 2003); a recent study of CEO succession in the world's largest 2,500 public companies revealed that in 2011 twenty-two percent of new CEOs came from outside their organization, compared to fourteen percent in 2007 (Booz & Co, 2011). Booz & Co (2011) showed that insider CEOs tend to serve for longer terms, and, that when they do retire, they leave their companies with higher shareholder returns compared with outsider CEOs (4.4 percent above the regional market index, as compared with 0.5 percent higher return). Much of the literature that examined insider and outsider CEOs revealed that different outcomes may be beneficial under different conditions -- dependent upon, for example, pre or post-succession firm performance, during periods of environmental munificence or turbulence, the level of strategic change that is introduced, and so on (Harris & Helfat, 1997; Karaevli, 2007; Zhang & Rajagopalan, 2010). New work on the expert leader hypothesis has been done in more-specialized settings (e.g. Goodall, 2009a,b; Goodall, 2011; Goodall, Kahn & Oswald, 2011).

In this paper we ask: when the core business activity of the firm aligns with the expertise of the leader, does that generate better organization performance? In Formula One, the core business is to win the Championship by gaining points in Grand Prix races. In our data, four leader-types are found: those who were formerly mechanics; those who were engineers (with degrees); former racing drivers; and, finally, individuals who were managers from other industries. Our performance data are on podium positions (that is, teams coming number 1-3 in a race). Podium places award a team the highest number of points, when compared to finishing lower down on a race day, and allow different teams to be compared in a consistent way.

Hypothesis 1: *Alignment between the expert knowledge held by the leader and the organization's core business activity is associated with better performance.*

Hypothesis 2: *Former racing drivers make the best leaders of F1 teams.*

Hypothesis 3: *The effect on performance of the former driving experience of the leader is larger than the effect of the driving experience of the current driver.*

3. Data and basic statistics

3.1 Formula One constructors

The dataset covers the performance of every team in every Grand Prix season since the industry began. This is for six decades of the F1 World Constructors' Championship between 1950 and 2011 (62 seasons) resulting in a total of 19,536 car entries in 858 races. We also collected background information about leaders of all F1 constructors (e.g. Ferrari, McLaren, Williams, Mercedes, etc.) for the same time period. The dataset enables us to measure exact organizational performance (over a 62 year period), and provides detailed measures of leader characteristics.

There are 106 constructor teams in these historical data. Since 1981, constructors have been obliged to build their own race car chassis, though not their engines. The goal of an F1 constructor is to maximize the number of points gained in races. In recent years each team entered two cars in consecutive races every year. Championship points are awarded based on the final position of each car at the end of the race (the first car wins the largest number of points, with other race points assigned, in a declining way, down to tenth position). Constructor teams are comparable in size. Identical criteria are applied to measure their performance.

We collected data on: the starting and final position of all cars that participated in each race; the constructor teams; their leaders' names, personal information and background; the drivers' personal information and background; and information about each race circuit. For a small number of years, information is also available on team budgets. The data were compiled from two main sources. For car entries, circuit, constructor, driver, as well as other detailed Grand Prix race information, we used the FORIX online database of Autosport magazine accessible on http://forix.autosport.com. The names and background information on each team leader were taken from the Grand Prix Encyclopedia website **http://www.grandprix.com**.[1]

In contrast to many industries where agents have greatly varying size and output, F1 constructor teams are fairly homogeneous in their size, capabilities, and approximate productivity. These characteristics make it scientifically a valuable industry for study. The higher is the position of the car in the final grid, the more points are awarded to its constructor team. Teams' common motivation means that relative comparison of teams' performance can be more exact than in settings where different companies make different products: the setting offers an unusual opportunity to compare organizations in a precise way. In addition, the core work-teams in F1 are relatively small (average of 400), which arguably allows a natural and suitable background against which to begin to try to understand the influence of leaders.

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[1] In some cases, when more detailed information for any particular leader was required, we have double-checked biographical information with information recorded in official biographies of leaders who currently hold positions on TV or in the Fédération Internationale de l'Automobile (FIA) – the F1 governing organization, and sometimes on Wikipedia.

In each racing season the number of constructor teams in the Championship can differ. For example, 21 teams competed in 1960, while only 12 were in the Championship in 2011. The decline in the number of competing teams seems primarily due to the cost associated with the sport which has increased over the years. If in 1950s and 1960s amateur mechanics could enter their self-made cars into races, current race car manufacturing requires long-term R&D investments and expensive testing, which is affordable only through a narrow circle of sponsors. The budgets of constructor teams are largely secret. Most of the money is spent on technology which contributes a great deal to a team's winning prospects (Read 1997, Wright 2001, Jenkins 2010). The R&D investment in F1 eventually shows up as new technologies in automobiles that the public drive.

3.2 The leaders (independent variable)

Leaders of constructor teams in F1, called principals, operate in a skilled and stressful environment which requires quick decision-making. The role of the leader in F1 is to run the team. Some differences exist in responsibilities between constructor teams; however, it is usual for the team leader to determine the long-term strategy of the constructor, to control technical matters, and to make the majority of financial decisions. Leaders also oversee the selection of drivers, who compete for their teams, and have a final say in making tactical decisions during each race. Some principals -- for example Frank Williams of Williams or Tony Fernandes of Team Lotus -- own and run their own teams. Owner-leaders have extensive powers. In other cases, principals are hired by owners to manage their teams. Such is the relationship between the beverage company Red Bull and principal Christian Horner. With large automobile manufacturers involved in racing, for example Mercedes, Renault and Ferrari, it is usual for a principal to be appointed, although their direct powers and responsibilities may vary across teams.

From our data, four types of leaders emerged. The taxonomy is as follows.

Managers typically spent most of their careers in business; they moved to F1 from a different (and often unrelated) industry. Manager-leaders tend not to have experience or education in car making or mechanical engineering or a connected field. They are also more likely to become involved in the industry relatively late in their careers.

Driver is assigned to leaders who competed in competitive racing (F1 and other competitions) as racing drivers, often from an early age (around 6-8 years old). Such leaders often started in Go-kart racing and then moved to professional racing by their early 20s. It is common for drivers to be familiar with the technical side of car making, as well as with mechanical aspects of car repairing, even though they do not have degrees in mechanical engineering or a related field. Drivers are usually the highest paid among team members.

Mechanics are those with practical technical experience in car making and mechanical repair. They tend not to have driven competitively, nor have they a degree in mechanical engineering or a related field. Mechanics often spent many years in automobile racing.

Finally, the term *engineer* is assigned to those with degrees in mechanical engineering. This is only an educational classification. It is does not imply that the individuals are or were involved in practical engineering matters within the racing organization. The information comes from their CVs.

Using this broad classification, leaders are fairly evenly distributed across the four background groups. More precisely, in the history of the industry there were 42 (29.8%) managers, 35 (24.8%) drivers, 31 (22.0%) mechanics, and 33 (23.4%) engineers. All leaders in our data were male.[2]

Despite what might be thought the possibility of ambiguity in leaders' classification, such cases are rare. For example, only 6 leaders out of the 141 had experience as both a driver and a mechanic. Several leaders had either multi-level experience or several industry experiences. In the few cases of doubt, leaders were assigned to their type according to the highest level of knowledge and primary area of activity.

We collected the population of entries into F1 World Constructors' Championship. Some minor omissions were inevitable. All team executives listed by the team as 'principal of the racing team' or 'team principal' could be identified as team leaders. Some teams in F1 history, however, were managed by several executives, i.e., by collective leaders. Since the focus of this paper is on individual leaders, we excluded those collective leaders from consideration (29 collective leaders, 1,351 car entries). In two further cases we were unable to identify team leaders or locate their biographical information. These observations were also excluded (460 car entries). The resulting dataset, therefore, contains information on 141 individual leaders who at different points of their lives represented 106 constructor teams and entered 17,725 cars into F1 World Constructors' Championship.

3.3 Grand Prix (dependent variable)

The number of races increased in a secular way from 7 in 1950 to 19 in 2011. As would be expected, a myriad of regulations apply in F1 to engine and chassis design, tires, tactics allowed by drivers and so on; noticeably, these rules sometimes changed from one season to the next[3]. This does not interfere with our statistical inference because the changed rules applied to every team in each championship. In the later econometric analysis, we control for the year of competition and therefore take into account these technical alterations from season to season.
F1 constructor teams' profits come from advertising and TV revenue.[4] F1 is the most widely watched sport after the Olympics and Football's World Cup, with over 500 million TV viewers in 2012[5]. A higher finishing position, primarily a podium (first to third), generates more sponsorship and TV income. Increasingly, modern teams are

[2] This is due to the fact that, until the year 2012, women never led F1 teams.
[3] Jenkins (2010) provides a detailed summary of these changes and their impact on F1 technology.
[4] See Formula Money website www.formulamoney.com for more details.
[5] Christian Sylt, theguardian.com, Friday 15 February 2013.

raising money from the development of F1 technologies that spill-over into other industries (McLaren have an associated company, Applied Technologies, as do Williams).

Table 1 (see next page) summarises the different championship point systems which have existed in F1 between 1950 and 2011.

Table 1: The relationship between F1 Champion points and the final position of cars

	Championship point system						
Final position	1950-1959	1960	1961-1990	1991-2002	2003-2009	2010-2011	1950-2011 (averages)
1st	8	8	9	10	10	25	11.7
2nd	6	6	6	6	8	18	8.3
3rd	4	4	4	4	6	15	6.2
4th	3	3	3	3	5	12	4.8
5th	2	2	2	2	4	10	3.7
6th	0	1	1	1	3	8	2.3
7th	0	0	0	0	2	6	1.3
8th	0	0	0	0	1	4	0.8
9th	0	0	0	0	0	2	0.3
10th	0	0	0	0	0	1	0.2

To allow a consistent measure of performance in the econometric analysis, we therefore use the relative final positions of cars in the race (instead of the number of obtained points). Since most points are awarded for podium positions (that is, for finishing 1, 2 and 3 in a particular race), we concentrate on winners of podium positions for each race. Using data on podiums also helps us to have a measure of success which is stable through the years of the industry.

3.4 Control variables

The regression analysis includes variables for other factors that may influence performance. We include controls for each race circuit (which may affect race performance due to a specific track shape or weather conditions). There are 71 race circuits in the dataset. Second, as mentioned above, a control is included for each year of competition (1950-2011); this adjusts for annual differences in the rules and regulations, which are factors that make F1 such a turbulent environment in which to compete. Third, we adjust for the number of cars competing in each race, because those numbers affect competitive pressure.

Finally, we control for each constructor's brand by allowing for team fixed effects. This is a particularly important feature of the analysis. Some constructors perform consistently better than others and that fact has to be incorporated into the estimation. For example, it might be that Ferrari or McLaren often outperform others not because they have successful leaders but because they have a long history of competing in F1 and thus traditionally had better facilities, more sponsorship money, intense public support, and highly experienced human resources. To calculate the influence of leaders, we need to control for these background differences. In the econometric analysis, therefore, a separate variable is included for each constructor brand (one for Ferrari, one for Red Bull, one for McLaren, etc.).

It might be expected that the amount of money each constructor spends would have an impact on outcomes. Unfortunately, teams do not release information about their budgets. Nevertheless, it has been possible for us to locate teams' financial investment for a small number of years. We include these results in a separate regression table in Appendix 2. Importantly, the table shows that inclusion of constructor money does not affect our key findings about leader type (see Appendix 2).

Explanatory variables used in our regression analysis are summarised in Table 2.

Table 2: Explanatory variables in the regression equations*

Explanatory variable	Description
CONSTANT	Constant
MANAGER	1 if the leader is classified as *manager*; 0 otherwise
DRIVER	1 if the leader is classified as *driver*; 0 otherwise
MECHANIC	1 if leader is classified as *mechanic*; 0 otherwise
ENGINEER	1 if the leader is classified as *engineer*; 0 otherwise
CIRCUIT	Each Grand Prix circuit has a different dummy
YEAR	Each year has a different dummy
TEAM	Each F1 constructor team has a dummy
# CARS	Number of cars qualified to race in any particular race

*All executives listed by the team as 'principal of the racing team' or 'team principal' are identified as team leaders. Those identified as having collective team leaders (more than one person) are excluded (29 leaders, 1,351 car entries). We also excluded 460 car entries in cases where we were unable to identify leaders.

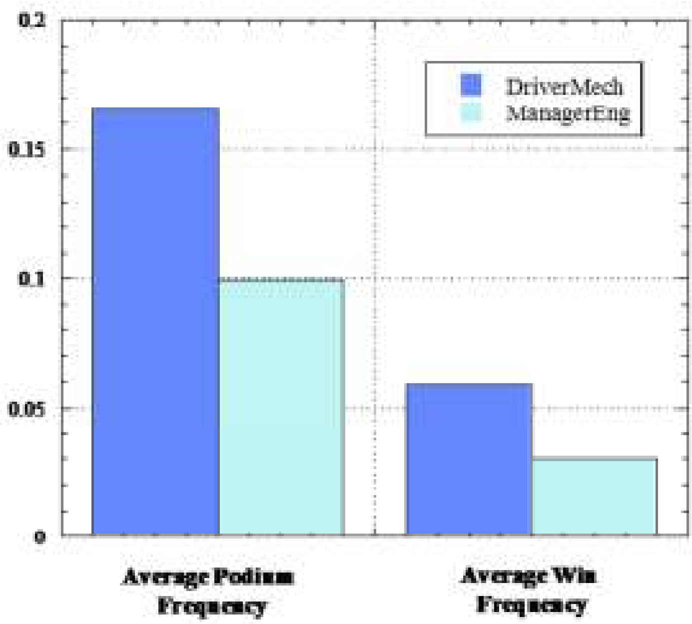
Descriptive statistics

Summary statistics are presented in Table 3. They show that between 1950 and 2011 the highest numbers of cars were entered by constructor teams led by former mechanics (7,456), which is explained by a statistical over-representation of mechanics in the early years of famous teams. The statistics reveal that podium frequency (i.e., winning a first, second or third place in a race) and average wins frequency (i.e., coming first in a race) are more prevalent among teams headed by drivers and mechanics as compared with managers or engineers. Drivers and mechanics also have higher average pole frequencies (finishing first in the qualifying, and, as a result, starting the race at the very front of the grid) and average fastest lap (showing the fastest time in the race on any given lap).

Table 3: Summary statistics of Formula 1 World Constructors' Championship 1950-2011

Leaders' type	Number of leaders	Number of cars	Average podium frequency	Average win frequency	Average pole frequency	Average fastest lap frequency
Managers	42	3,498	0.12	0.03	0.03	0.04
Drivers	35	2,779	0.17	0.07	0.07	0.06
Mechanics	31	7,456	0.16	0.06	0.05	0.06
Engineers	33	3,992	0.08	0.03	0.03	0.03
Total	141	17,725	0.14	0.05	0.05	0.05

Figure 1: Average podium frequency (1-3) and win frequency of F1 leaders who were drivers or machanics (DriverMech) compared with leaders who were managers or engineers (ManagerEng)



*Results of Wilcoxon-Mann-Whitney test show that the differences between win frequencies and podium frequencies of leaders classified as drivers or mechanics versus leaders classified as managers or engineers are statistically significant. The Wilcoxon-Mann-Whitney z-statistics for podiums is equal to -12.509 (prob<0.0001). The Wilcoxon-Mann-Whitney z-statistics for wins is equal to -8.901 (prob<0.0001).
Note: A simple OLS regression with 141 observations also shows that drivers or mechanics are more likely to achieve podiums during their career than managers or engineers (significant at 0.05 level).

In our dataset, the mean propensity to gain a podium position is 0.14 and the standard deviation is 0.34. Therefore, on average, a constructor team has a 14% chance per race of winning a podium.

The mean values in Columns 4 and 5 of Table 3 reveal that the most successful leaders were former drivers closely followed by mechanics. Drivers are associated with a winning team in 7% of races, and they garner a podium position in 17% of races. The performance of teams led by mechanics is similar (winning 6% of the time, and getting podiums 16% of the time). Teams headed by leaders of a manager type obtain worse results: they win 3% of races and obtain podium positions in 12% of the races. Constructor teams led by engineers fare even less well: 3% wins and 8% podiums. Similar patterns are found for average pole frequency and average fastest lap frequency. These findings are represented in Table 3 and Figure 1.

Although the raw patterns reported in Table 3 are of interest, they should not be interpreted in too literal a way. The data provide a preliminary summary without accounting for any control variables. Those variables potentially have an important impact on teams' performance and, therefore, may interact with leaders' types.

4. Econometric Analysis and Results

In this section we use econometric analysis to test the hypotheses in Section 2.

4.1 The impact of leader types on organizational performance

We explore whether constructor teams' performance in F1 depends on leaders' types. In each of the regressions, the dependent variable is a measure of the performance of the team based on the final position of each car in every race. The key explanatory variable is a leader's classification (that is: manager, driver, mechanic or engineer). Finally we include control variables for each constructor, the race track, the number of cars competing and each race year.

As reported earlier, the raw data revealed a simple pattern: that two leader-types appear to be associated with the most wins and podium positions. We therefore begin with a preliminary analysis by dividing the data into these two groups: drivers and mechanics, and managers and engineers. We begin with a simple ordinary least squares (OLS) estimator. Model 1 in Table 4(a) reports an OLS regression model without control variables and then provides results with controls in Models 2-5. Table 4(a) treats the data in a cardinal way and estimates an ordinary least squares linear probability model. The dependent variable $\pi_i \in \{0,1\}$ records whether a particular car i has won a podium in a race ($\pi_i = 1$) or did not win a podium in the race ($\pi_i = 0$).

Table 4(a): Regression results where the dependent variable is whether a car gets a podium position – estimated by an OLS linear probability model

Explanatory variable	**Model 1 coefficient (standard error)**	**Model 2 coefficient (standard error)**	**Model 3 coefficient (standard error)**	**Model 4 coefficient (standard error)**	**Model 5 coefficient (standard error)**
Driver or mechanic	0.066*** (0.005)	0.066*** (0.005)	0.066*** (0.005)	0.042*** (0.008)	0.044*** (0.0083)
Manager or engineer	-	-	-	-	-
CIRCUIT dummies included	NO	YES	YES	YES	YES
YEAR dummies included	NO	NO	YES	YES	YES
TEAM dummies included	NO	NO	NO	YES	YES
# CARS included	NO	NO	NO	NO	YES
R^2	0.0088	0.0102	0.0103	0.1305	0.1308
N (Observations)	17725	17725	17725	17725	17725
N (Leaders)	141	141	141	141	141

*** - significant at 0.001 level

The mean of the dependent variable (gaining a podium position) is 0.14.

Table 4(b): Regression results where the dependent variable is whether a car gets a podium position – estimated by a multilevel probit model

Explanatory variable	**Model 1 coefficient (standard error)**	**Model 2 coefficient (standard error)**	**Model 3 coefficient (standard error)**	**Model 4 coefficient (standard error)**	**Model 5 coefficient (standard error)**
Driver or mechanic	0.418*** (0.039)	0.502*** (0.033)	0.544*** (0.036)	0.478*** (0.035)	0.384*** (0.036)
Manager or engineer	-	-	-	-	-
Individual leader's effect st. deviation (st. error)	0.481 (0.004)	0.572 (0.005)	0.398 (0.024)	0.516 (0.004)	0.693 (0.011)
CIRCUIT dummies included	NO	YES	YES	YES	YES
YEAR dummies included	NO	NO	YES	YES	YES
TEAM dummies included	NO	NO	NO	YES	YES
# CARS included	NO	NO	NO	NO	YES
Log likelihood (LL)	-5979.23	-5972.18	-5956.03	-5947.43	-5926.49
N (Observations)	17725	17725	17725	17725	17725
N (Leaders)	141	141	141	141	141

*** - significant at 0.001 level

The remaining columns of Table 4(a) report specifications after we add control variables to the basic regression analysis. These include the circuit where the race is taking place, the year of competition, the constructor team a particular car represents, and finally, the total number of cars that participate in the race.

Column 2 of Table 4(a) reveals that after controlling for the circuit, it is drivers and mechanics compared with managers and engineers that are associated with a higher propensity of winning a podium position: the t statistic is 12.50 ($p<0.001$). In columns 3-5 as we add more controls for the year of competition, constructor team dummies, and number of cars in each race, the results remain stable. Overall, Table 4(a) shows that drivers and mechanics are associated with better organizational performance compared with managers and engineers.

Results of the basic analysis reported in Table 4(a) do not allow us to single out how much of an effect individual leaders' unobserved heterogeneity has on the propensity of constructor teams to gain podium positions controlling for leader types. The dataset has a specific form: each leader (within each constructor team) enters two cars in multiple races within each year. Some leaders (constructor teams) compete in many seasons whereas others drop out after participating in the Championship for one year. Therefore, our dataset represents an unbalanced panel which has more than one observation for each leader within each time period. So that we can incorporate individual underlying differences (unobserved heterogeneity) at the level of each leader -- to account for the binary nature of the dependent variable (winning or not winning a podium position) and to make use of the complex structure of our panel dataset -- we use a multilevel probit regression specified in the following way (see Snijders and Bosker, 1999 for details).

Assume that the dichotomous dependent variable θ is produced by a threshold model with underlying variable $\tilde{\theta}$ given by

$$\tilde{\theta} = \beta_0 + \sum_{k=1}^{n} \beta_k x_{kij} + u_j + \varepsilon_{ij} \quad (1)$$

where $x_1 \dots x_n$ are explanatory variables; β_0, $\beta_1 \dots \beta_n$ are coefficients. Variance σ_ε^2=1 and the variance of the random intercept σ_u^2 is estimated jointly with the coefficients. Log-likelihood is approximated using Gauss–Hermite quadrature. Results of the multilevel probit regression are reported in Table 4(b).

Table 4(b) shows that results of the multilevel probit regression are qualitatively similar to the results of the simple OLS models presented in Table 4(a). Teams led by former drivers or mechanics are more likely to achieve podiums than teams headed by former managers or engineers. This suggests that the effect of driver or mechanic leader type on team output remains the same even when we control for the individual differences of leaders.

We also estimate the effect of each leader type (managers, drivers, mechanics and engineers) separately. We run models with unobserved individual heterogeneity at the level of each leader. Table 5(a) reports the results of the probit estimations which include several confounding variables (shown in Table 2). In these estimations, we are interested in determining the probability of team leaders with different backgrounds (manager, driver, mechanic, and engineer) securing a podium position for their teams. The impact of leaders' types on propensity to gain a podium position (1-3) is measured compared to that of manager (the omitted base category).

Table 5(a): Regression equations where the dependent variable is whether a car gains a podium position - estimated by a probit model

Explanatory variable	Model 1 coefficient (standard error)	Model 2 coefficient (standard error)	Model 3 coefficient (standard error)	Model 4 coefficient (standard error)
MANAGER				
DRIVER	0.202*** (0.040)	0.205*** (0.040)	0.292*** (0.062)	0.300*** (0.062)
MECHANIC	0.197*** (0.033)	0.191*** (0.033)	0.021 (0.063)	0.035 (0.063)
ENGINEER	-0.242*** (0.040)	-0.252*** (0.041)	-0.115 (0.071)	-0.118 (0.072)
CIRCUIT dummies included	YES	YES	YES	YES
YEAR dummies included	NO	YES	YES	YES
TEAM dummies included	NO	NO	YES	YES
# CARS included	NO	NO	NO	YES
Pseudo R^2	0.0156	0.0160	0.1404	0.1409
N (Observations)	17725	17725	17725	17725
N (Leaders)	141	141	141	141

*** - significant at 0.001 level

Table 5(b): Regression equations where the dependent variable is whether a car gains a podium position - estimated by a multilevel probit model

Explanatory variable	Model 1 coefficient (standard error)	Model 2 coefficient (standard error)	Model 3 coefficient (standard error)	Model 4 coefficient (standard error)
MANAGER				
DRIVER	0.249*** (0.057)	0.237*** (0.055)	0.134* (0.059)	0.134** (0.062)
MECHANIC	0.046 (0.048)	0.185*** (0.048)	0.430*** (0.059)	0.429*** (0.060)
ENGINEER	-0.337*** (0.058)	-0.158*** (0.056)	-0.211*** (0.063)	-0.210*** (0.063)
Individual leader's effect st. deviation (st. error)	0.506 (0.004)	0.700 (0.011)	0.569 (0.007)	0.699 (0.010)

CIRCUIT dummies included	YES	YES	YES	YES
YEAR dummies included	NO	YES	YES	YES
TEAM dummies included	NO	NO	YES	YES
# CARS included	NO	NO	NO	YES
Log-likelihood (LL)	-5938.10	-5940.73	-5912.69	-5910.48
N (Observations)	17725	17725	17725	17725
N (Leaders)	141	141	141	141

* - significant at 0.05 level; ** - significant at 0.01 level; *** - significant at 0.001 level

In Table 5(a), the probit model in Column 1 controls only for each Grand Prix circuit (71 circuits). Compared to managers, teams headed by drivers are statistically more likely to win a podium position, irrespective of the influence of the circuit. The coefficient is slightly greater than 0.20 (z-statistic 5.09, $p<0.001$). Mechanic-leaders are a little less influential – coefficient is less than 0.20 and z-statistic 6.01, $p<0.001$). In Table 5(a) engineers have a statistically significantly negative effect on obtaining first, second or third place in a Grand Prix (coefficient approximately -0.24; z-statistic -5.99, $p<0.001$).

Column 2 of Table 5(a) extends the set of independent variables. It includes controls for both the circuit and each year in our dataset (1950 to 2011). This new addition of the year dummies does not change the results appreciably. Drivers and mechanics have a statistically significant effect on the probability of a podium position, whereas engineers have a negative influence.

The results change noticeably in the specification of Column 3 in Table 5(a). Here we include constructor dummies. Teams like Ferrari show up strongly – with large coefficients. Between 1950 and 2011 Ferrari won 16 World Constructors Championships – more than any other team in the history of F1. The constructors' effects on race performance are evident in the seven-fold increase in the pseudo-R^2 which rises in Table 5(a) from approximately 0.02 in Columns 1 and 2, to 0.14 after the addition of team fixed-effects.

Column 3 of Table 5(a) illustrates an important finding: drivers now have a statistically significant and positive effect on the probability of a podium position; the effect of mechanic-leaders is now insignificant, while engineer-leaders remain negative and insignificant. In this estimation, the coefficient on drivers goes up slightly and equals to approximately 0.29 (z-statistic 4.71, $p<0.001$). The results in the last column of Table 5(a), with the inclusion of the fourth potential confounding variable -- the number of cars qualifying in each race -- remains similar to those in Column 3**.** We check the robustness of our results by estimating several multilevel probit models. These results are qualitatively similar, but quantitatively different, to those reported in Table 5(b).

In Table 5(b), the coefficient on Mechanic is now considerably larger, at 0.429. These results are now reminiscent of the simple patterns in the raw data earlier, where both drivers and mechanics were associated with better performance. The fact that the coefficients move around suggests that it may be asking too much of the data to expect to isolate persuasively the exact sizes of the effect for the four different categories.

4.2 The impact of the length of leader's racing experience on performance

The findings in Tables 4-5 suggest that former drivers and mechanics are statistically more likely to lead their constructor teams to win podium positions. Our hypothesis that improved performance is associated with leader-characteristics that most closely align with the core business activity can now be examined in a new test. Here the focus is on the number of years leaders spent in competitive racing. This might be viewed as akin to executive tenure, which the upper echelons literature suggests can be used as a proxy for a number of factors (for example, cognition, knowledge, interest and power), that influence a leader's decision making and performance (Hambrick and Fukutomi, 1991). The results from our time-in-industry estimations are reported in Table 6.

We identify those leaders who have ever had competitive driving experience. Thirty-five leaders (24%), from a total of 141 in our dataset, are classified as drivers; however, 45 leaders (33%) have driven competitively at some point in their life (this number includes 35 former drivers, 7 mechanics, 2 managers, and 1 engineer). To explore whether such experience might be the main determining factor of a team's success, we conduct several econometric estimations.

A potential concern is unobserved heterogeneity of leaders on performance (that is, leaders may differ in subtle ways that are not easily measured by statistical investigators). This study proposes to solve this problem by conducting a random-intercept logit regression. The dependent variable is binary $\pi_i^t \in \{0,1\}$ and represents podium or no podium position gained at time t by constructor team i. The probability that team i wins a podium position in period $t \in [1, T]$ is given by:

$$P(\pi_i^t = 1) = \frac{exp(\beta_1 X1_i^t + \beta_2 X2_i^t + \cdots + \beta_M XM_i^t + \alpha_i)}{1 + exp(\beta_1 X1_i^t + \beta_2 X2_i^t + \cdots + \beta_M XM_i^t + \alpha_i)} \qquad (2),$$

where $\boldsymbol{X1_i^t}$ is the leader's years of experience as a competitive driver in the past and $\boldsymbol{X2_i^t} \ldots \boldsymbol{XM_i^t}$ are explanatory variables described in 3, $\boldsymbol{\beta_1} \ldots \boldsymbol{\beta_M}$ are marginal effects and $\boldsymbol{\alpha_i}$ is a vector capturing unobserved individual heterogeneity at the level of every leader in each season. The conditional log-likelihood function of the random intercept logit regression has the following form:

$$LL = \prod_{i=1}^{N} \int_{-\infty}^{+\infty} \prod_{t=1}^{T} \left(\frac{exp(\beta_1 X1_i^t + \beta_2 X2_i^t + \cdots + \beta_M XM_i^t + \alpha_i)}{1 + exp(\beta_1 X1_i^t + \beta_2 X2_i^t + \cdots + \beta_M XM_i^t + \alpha_i)} \right) f(a) da \qquad (3)$$

The log-likelihood function (2) is approximated using the Newton-Raphson method.[6] Results of the random intercept logit regressions estimated with different number of explanatory variables are reported in Table 6 where the dependent variable is obtaining a podium position.

Table 6: Regression equations where the dependent variable is whether a car gains a podium position -- estimated by random intercept logit model -- in the subsample of leaders who have ever had competitive driving experience[1]

Explanatory variable	**Model 1 marginal effect (standard error)**	**Model 2 marginal effect (standard error)**	**Model 3 marginal effect (standard error)**	**Model 4 marginal effect (standard error)**	**Model 5 marginal effect (standard error)**
Leader's years of experience as a competitive driver in the past	0.106*** (0.012)	0.115*** (0.014)	0.113*** (0.013)	0.072*** (0.021)	0.073*** (0.022)
Leader in each season individual effect:st. deviation (st. error)	1.854 (0.302)	1.833 (0.276)	1.598 (0.220)	1.050 (0.127)	1.103 (0.135)
CIRCUIT dummies included	NO	YES	YES	YES	YES
YEAR dummies included	NO	NO	YES	YES	YES
TEAM dummies included	NO	NO	NO	YES	YES
# CARS included	NO	NO	NO	NO	YES
Log likelihood (LL)	-1617.88	-1596.03	-1599.18	-1494.93	-1494.93
N (Observations)	6061	6061	6061	6061	6061
N (Leaders)	45	45	45	45	45

*** - significant at 0.001 level

[1] The data include 45 leaders out of 141 (33%) who have entered 6,061 cars in 803 out of 858 races in F1 competitions between 1950 and 2011. These are leaders who have ever had a competitive driving experience. Out of them, 35 are classified as drivers, 7 as mechanics, 2 as managers, and 1 as engineer.

Interestingly, in Table 6, the length of the previous experience of the leader has a positive effect on performance in all estimations. Overall, leaders' unobserved heterogeneity within each race accounts for about 30% of variation in winning a podium position when we do not control for the constructor team (e.g., standard deviation of variability of leader's individual effects are equal to 0.302 in Model 1 in Table 6. However, once we add controls for the constructor teams, the individual effect of each leader within each race decreases significantly suggesting that accounting for constructor team is very important (e.g., standard deviation of variability of leader's individual effects are equal to 0.135 in Model 5 in Table 6.

[6] The estimation has been conducted using the GLLAMM plug-in for the Stata 10.0 package.

A further check is whether there is a home-race effect. One of our regression variables allows us to control for the impact of a specific circuit. The home-race effect accounts for the possibility that constructors may have competitive advantage if the race circuit is located in the same country where the team headquarters is located. Constructors may be more likely to win a podium position in their home country (country where their headquarters are located). To control for the home-race effect, we first compare the frequencies of winning a home race versus winning a race abroad for our entire sample of car entries. We find no relationship between the average frequency of winning a podium position at home as compared with abroad.[7]

4.3 The impact of the leader on the key follower – the driver

To this point, the analysis has suggested that the length of leader's previous experience in competitive driving has a significant positive impact on organizational performance in F1 constructor teams: the higher is a leader's experience as a driver in the past, the more likely his team is to win a podium position in a given race. Yet, it is interesting to consider the impact of leader's previous experience on team performance not only separately, but also in conjunction with the performance of key followers (drivers who compete for the team).

In recent years, constructor teams compete with two cars in each Grand Prix race; however, the number of cars per team has varied throughout F1 history between 1 and 2. Since each observation in our dataset is a car entry, driven by a particular F1 driver and representing a specific F1 constructor team, which takes part in the F1 Constructor Championship, we can look at a combination of leader-driver performance for each entry in our dataset. We consider the length of a leader's experience as a competitive driver in the past in conjunction with the length of experience of drivers who currently compete for this leader's team. We look at each current driver's experience as a competitive driver in F1.[8]

For one leader in the dataset, it was not possible to identify drivers. We have thus excluded those 7 car entries from the analysis. Therefore, the resulting data for the analysis of leader-driver experience combinations consisted of 140 leaders, 662 drivers, and 17,718 car entries.

In the remaining dataset, there is considerable individual heterogeneity in terms of length of experience both among 140 leaders (the length of experience ranges from no experience to 17 years of experience with the mean of 7.3 years, standard deviation of 5.1 years and the median of 7 years) and 662 drivers (the length of experience also ranges from no experience to 17 years of experience with the mean of 3.8 years, standard deviation of 3.4 years and the median of 3 years). In order to simplify the analysis and construct a sensible number of leader-driver experience

[7] Tables and estimations reporting this result are available from the authors upon request.

[8] Note that while a leader's experience is measured as number of years a leader participated in various competitions (not only F1) as a competitive driver before becoming an F1 team principal. At the same time, a current driver's experience is measured as an experience of a particular driver in F1 competition to the date of a given race.

combinations, we identify 3 cohorts of leaders and 3 cohorts of drivers dependent on the length of their experience.

We distinguish between the following cohorts of leaders:

- **L**eader **N**one (dr) – leader's previous experience as a competitive driver is equal to 0 years;
- **L**eader **M**edium (dr) – leader's previous experience as a competitive driver is equal to 1 to 5 years;
- **L**eader **L**ong (dr) – leader's previous experience as a competitive driver is greater than 5 years.

At the same time, we identify 3 cohorts of drivers:

- **D**river **N**one – driver's previous experience as a competitive driver in Formula 1 is equal to 0 years;
- **D**river **M**edium – driver's previous experience as a competitive driver in Formula 1 is equal to 1 to 5 years;
- **D**river **L**ong – driver's previous experience as a competitive driver in Formula 1 is greater than 5 years

While each leader's cohort does not change throughout the dataset (because we take into account leaders' experience before they have become principals in F1), drivers may move from the cohort DN to the cohort DM and then to the cohort DL throughout the dataset (because they gain experience from one year to the next as long as they stay in F1). Given these cohorts, we can identify 9 combinations of leader-driver experiences:

1. LN(dr)-DN: 1654 (9%) experience combinations from 1950 to 2011;
2. LN(dr)-DM: 615 (3%) experience combinations from 1950 to 2011;
3. LN(dr)-DL: 530 (3%) experience combinations from 1950 to 2011;
4. LM(dr)-DN: 6710 (38%) experience combinations from 1950 to 2011;
5. LM(dr)-DM: 1547 (9%) experience combinations from 1950 to 2011;
6. LM(dr)-DL: 2020 (11%) experience combinations from 1950 to 2011;
7. LL(dr)-DN: 3296 (19%) experience combinations from 1950 to 2011;
8. LL(dr)-DM: 276 (2%) experience combinations from 1950 to 2011;
9. LL(dr)-DL: 1070 (6%) experience combinations from 1950 to 2011.

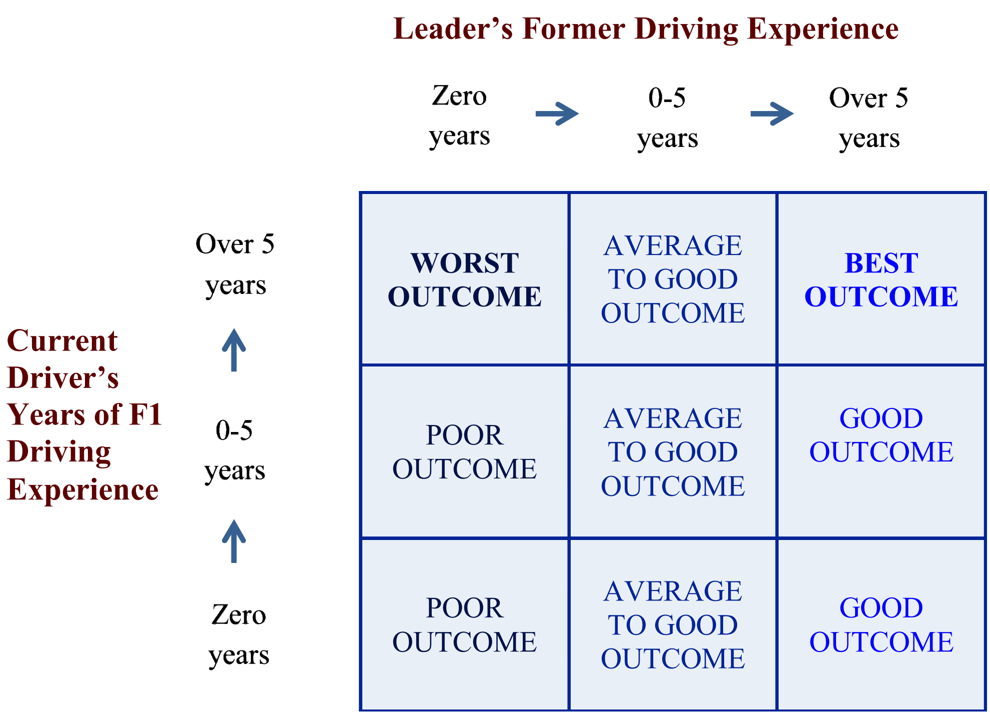
To explore the extent to which these effects are observed in the data, we conduct a clustered conditional logit regression without and with control variables (circuit individual effects, year of competition, constructor individual effects, number of cars in a race). The dependent variable is the correlation between podiums and combinations of leader-driver experience (a categorical variable with base category combination LN(dr)-DN). Standard errors are clustered at the level of each individual leader (140 clusters in our dataset). Results of these clustered logit regressions are reported in Table 7.

Table 7: Results of clustered conditional logit regression without and with controls (correlation between podiums and combinations of leader-driver experience). Leader's experience is measured as leader's previous experience as competitive driver.
Base category: combination LN(dr)-DN.
[Dependent variable: whether a car won a podium position or not]

Combination	**Model 1 coefficient (robust standard error)**	**Model 2 coefficient (robust standard error)**	**Model 3 coefficient (robust standard error)**	**Model 4 coefficient (robust standard error)**	**Model 1 coefficient (robust standard error)**
LN(dr)-DN	-	-	-	-	-
LN(dr)-DM	-0.6589917 (0.7469524)	-0.6775477 (0.7252807)	-0.6620999 (0.7095704)	-0.2799302 (0.4221312)	-0.2731413 (0.4182238)
LN(dr)-DL	-2.092188*** (0.415654)	-2.048483*** (0.4251668)	-1.986393*** (0.4528088)	-0.7888245 (0.549179)	-0.7760258 (0.538188)
LM(dr)-DN	1.037523*** (0.1839944)	1.066706*** (0.1802005)	1.089532*** (0.1794364)	0.6934863*** (0.2026239)	0.695632*** (0.2015751)
LM(dr)-DM	0.8386818† (0.4902904)	0.8324678† (0.478085)	0.8398051† (0.4633605)	0.8348534* (0.396006)	0.8328638* (0.3944819)
LM(dr)-DL	0.7735891† (0.4166392)	0.8230227* (0.425948)	0.8759659* (0.4386714)	1.312192*** (0.2432113)	1.324331*** (0.2390952)
LL(dr)-DN	1.353978*** (0.1951035)	1.408388*** (0.1784429)	1.45925*** (0.1730723)	0.8919771*** (0.2145238)	0.9091598*** (0.2125711)
LL(dr)-DM	0.565194 (0.7308702)	0.5926472 (0.7375657)	0.6422772 (0.728222)	0.8009291 (0.5251208)	0.8203238 (0.5367398)
LL(dr)-DL	1.474793* (0.7149445)	1.518909* (0.7060216)	1.594736* (0.7115901)	1.529971*** (0.3816751)	1.525973*** (0.3739136)
CIRCUIT dummies included	NO	YES	YES	YES	YES
YEAR dummies included	NO	NO	YES	YES	YES
TEAM dummies included	NO	NO	NO	YES	YES
# CARS included	NO	NO	NO	NO	YES
Pseudo R^2	0.0322	0.0348	0.0358	0.1497	0.1500
N (Observations)	17718	17718	17718	17718	17718
Clustered at the level of individual leader (140 clusters)	YES	YES	YES	YES	YES

Abbreviations: LN(dr) – leader's previous experience as competitive driver is equal to 0 years;
LM(dr) – leader's previous experience as competitive driver is equal to 1 to 5 years;
LL(dr) – leader's previous experience as competitive driver is greater than 5 years;
DN – driver's previous experience as competitive driver in Formula 1 is equal to 0 years;
DM – driver's previous experience as competitive driver in Formula 1 is equal to 1 to 5 years;
DL– driver's previous experience as competitive driver in Formula 1 is greater than 5 years
Significance: † - significant at 0.10 level; * - significant at 0.05 level; ** - significant at 0.01 level; *** - significant at 0.001 level

Figure 2: Matrix showing the interaction between leaders' racing experience and the F1 racing experience of their current team drivers



According to Table 7, the combination LL(dr)-DL is more likely to win a podium position than any other combination. Combinations where leaders have medium or long previous driving experience are more likely to reach podiums than combinations where leaders do not have previous driving experience. Furthermore, regression results suggest that leaders' experience as a competitive driver in the past seems to matter more than the F1 racing experience of the current drivers. In Model 5 with all 4 control variables, the coefficients for combinations with LN(dr) range between -0.78 to -0.27, whereas the coefficients for combinations with LM(dr) range between

0.83 and 1.32 and coefficients for combinations with LL(dr) range between 0.82 and 1.53.[9]

The results tell us that highly experienced leaders paired with highly experienced drivers (combination LL(dr)-DL) gain podiums in 21% of cases (more frequently than any other leader-driver combination). However, it is notable that when a highly experienced leader is paired with a rookie driver (combination LL(dr)-DN), the team reaches podium positions in 19% of cases. This finding is noteworthy because it suggests, first, that only a small difference exists between pairing an experienced F1 driver with a driver-leader (2%), and, second, that leaders with previous driving experience work more effectively with rookie drivers than with those who have 1 to 5 years of driving experience in F1. For ease of comprehension, the regression results have been represented in a matrix in Figure 2.

5. Discussion

The evidence presented above reveals that over the six decades of the Formula One global industry it is leaders who were former drivers who had the greatest later success. To understand why and how driver-leaders might affect performance is an empirical issue; our dataset does not allow us to causally uncover the underlying details of the transfer processes. Nevertheless, it is interesting to raise further questions and possible explanations that might be considered in future empirical work (Goodall & Bäker 2013).

Our data exclude important information -- for example, management skills, which are positively associated with organizational performance (Bloom & Van Reenen, 2007; Bloom, Genakos, Martin & Sadun, 2010). It is natural to assume that F1 principals vary in their individual management and leadership skills.

Might drivers make better leaders because of (unmeasured) personality as opposed to expert knowledge?[10] This is an important conceptual possibility and it seems valuable that future research attempt to scrutinize it in depth. But a number of pieces of evidence currently appear to point against such an interpretation.

It is not feasible to measure the personality types of each driver -- many of whom are no longer alive -- in this historical dataset. However, one reason to be cautious about the hypothesis of an overwhelming influence from personality is that former mechanics also perform well as F1 principals. It is not clear why the personality of mechanics and drivers would be similar to each other. Second, and perhaps more important, within the sub-sample of everyone who ever drove we find that individuals with the longest racing experience make the best leaders. This seems powerfully suggestive of the role of mature expertise rather than solely of personality (though personality might be somewhat implicated in the ability to be driver for a large rather than medium number of years). When a leader has 10 years

[9] The same results are obtained in regressions where the dependent variable is the propensity to win a race.
[10] We would like to thank an anonymous referee for this suggestion.

of racing experience instead of zero years, it translates, according to the data, into a 16 percentage points higher probability of the leader's team gaining a podium position – this is after controlling for the race circuit, the race year, each constructor, and the number of cars that qualified. If race drivers have similar personality traits we would not expect such large differences within the group. Finally, we can run an empirical test that may add weight to the arguments in support of knowledge over sheer personality. We can ask: do drivers who are in constructor teams led by former-drivers, versus other leaders, crash less or more in Grand Prix races? We find that cars in teams led by leaders with no previous driving experience on average a crash in 12%-15% of cases, whereas cars in teams led by leaders with high levels of experience crash in 10%-13% of cases[11]. Caution is necessary here when drawing conclusions, but one interpretation is that this interaction result may be explained by expert knowledge -- in a way quite independent of personality -- that is transferred from the leader to the way the team performs.

The core business activity in F1 is racing to win championship points. We label expert leaders as those whose knowledge and experience aligns with the organization's core business activity. Examples include: university presidents who have strong research records who lead research universities (Goodall 2009a,b); basketball coaches who were themselves star players in the NBA (Goodall, Kahn & Oswald. 2011), and so on. We suggest that former drivers are highly competent in the core business activity of racing.

That drivers are important to F1 constructors is evident in their wages[12]. It is usual for drivers to receive the highest salaries in F1 teams. Drivers occupy a unique position in the team because they can view all elements of the F1 process; it is the drivers who feed back information about new adaptations to the chassis, engine, tires and other car modifications after races. Drivers also form relationships with all parts of the team and they are often involved with raising money; indeed some are required to come with their own sponsorship package.

It is normal for drivers to begin racing at an early age, usually after go-karting as children. Because of their early competitive start, drivers may develop both technical knowledge and driving tactics that are combined with an ability to make decisions under time pressure and stress. It might also be presumed that a leader who has spent time undertaking the core business activity would have a good understanding about the requisite conditions required for other core workers. Thus, we might expect driver-leaders to create an appropriate work environment, which in turn may influence employee performance. This is supported by findings from the creativity literature that suggests leaders need technical expertise to evaluate the ideas of other creative people and provide appropriate feedback (summarized by Mumford et al., 2000; Basadur, Runco, & Vega, 2000).

[11] We use a Kruskal-Wallis test and find statistically significance at 0.0004 level. Due to space restrictions we have not included a table.

[12] Salaries for 2013 available at: http://www.tsmplug.com/richlist/highest-paid-formula-1-drivers/

Former drivers who lead may also act as role models within the team, and may be more likely to coax high performance out of others. In the context of North American professional basketball, Goodall et al. (2011) argued that having been a former top basketball player helps those who become coaches to better manage the egos of their top players. Finally, because of their proven track record, former drivers may command more respect; they may be viewed as intrinsically credible since they have 'walked-the-walk'. Credibility, it is argued, legitimizes leaders' authority and extends their influence (Bass, 1985; Bennis & Nanus, 1985; Kouzes & Posner, 2003).

This study contributes to the growing literature examining the influence of leaders on organizational performance. A number of scholars have claimed that leaders have a sizeable effect (Thomas 1988; Finkelstein & Hambrick, 1996; Waldman & Yammarino, 1999; Bertrand & Schoar, 2003; Jones and Olken 2005; Bennedsen, Perez-Gonzalez and Wolfenzon 2007; Yukl, 2008; Pogrebna et al., 2011; Kocher, Pogrebna & Sutter, 2013; Souder, Simsek & Johnson, 2012; Dezs & Ross, 2012). In this literature the explanatory power from CEOs has typically ranged from 4% (Thomas, 1988) to 15% (Wasserman et al., 2010) up to 30% (Mackey, 2008). Here we also find large effects. The influence of former drivers, the most successful leaders in our study, explains 17% (in the raw data) of organizational performance (podium position, 1-3).

6. Conclusion

This paper takes a new step to understand the boundaries of the expert leader hypothesis by testing it in an extreme high-technology turbulent industry -- a setting where leadership has not before been examined. Formula One could be viewed as the iconic, modern, hyper-competitive, global industry. The dataset that we collected for this study provides longitudinal information on that industry's entire history. The dataset also offers the unusual advantage of half a century of objective organizational outcomes against which to determine the kinds of leaders associated with optimal performance. The F1 industry is important financially ($6 billion turnover per annum) and competition on the track generates new technologies that spill over into many parts of the economy.

We have information on every leader in the 62 year history of Formula One, 1950-2011. Four leader classifications emerge from our data: engineers who have degrees, managers who come from industries outside F1, mechanics, and former racing drivers. We test our propositions, described in section 2, using econometric methods. These methods allow us to compare teams' performance and determine whether and to what extent leaders' competence in the core business activity (especially driving) affects later team performance. We include a number of control variables in the analyses -- the race circuit, the race year, the different constructors (Ferrari, McLaren, Red Bull etc.), and the number of cars qualified. In general, teams have historically not released information about their budgets. However, we identified teams' financial investment for a small number of years, and we show that inclusion in our equations of a variable for the constructor's budget does not affect the study's key findings.

Managers and engineers on average perform least successfully as F1 team leaders. Principals who were mechanics performed well, though less well overall compared with former drivers. In our regression tables we find, first, that F1 leaders who were former racing drivers and mechanics are associated with the most success in winning podium positions in Grand Prix races. Second, among the sub-sample of leaders who have ever driven competitively, it is leaders who spent the most years racing -- arguably the most successful drivers -- who secure the best results for their F1 teams. We argue that a long racing career might be viewed as an equivalent to, or proxy for, executive tenure or time-in-industry. The size of the estimated effect is noteworthy: 10 years of experience instead of zero years is associated with an extra 0.16 on the dependent variable. That translates into a 16 percentage point higher probability of the leader's team winning a podium position (after the inclusion of control variables for race track, race year, constructor type, and number of cars). The extra probability of gaining a podium position when a driver has had a decade's experience of competitive racing is about one-in-seven, which corresponds to a doubling of the effect compared with the mean podium frequency in the data of 0.14.

Finally, and perhaps notably, we attempt to discern the effects that different leaders have on what might be considered their key employees – the team drivers. To do this, we interact leaders' formers driving experience with the F1 racing experience of the current team driver. The evidence suggests that in most circumstances the driving experience of the principal matters more to team performance than the F1 driving experience of the current driver. A highly experienced driver-leader paired with a highly experienced F1 driver gains podiums in 21% of cases (more frequently than any other leader-driver combination). However, when a highly experienced driver-leader is paired with a rookie driver, the team reaches podium positions in 19% of cases. This finding seems striking because it suggests, first, that only a small difference exists between pairing an experienced F1 driver with a driver-leader (2%), and, second, that leaders with previous driving experience work more effectively with rookie drivers than with those who have 1 to 5 years of driving experience in F1. Leaders who have never raced have the least influence, no matter how much F1 racing experience their driver previously achieved. This is an interesting result because it is a sharp signal that leaders matter.

Within the limitations of our historical dataset we cannot explain precisely why the F1 leaders who were drivers outperformed other leaders in the six decades of F1. Nevertheless, we discuss possible explanations. For example, we suggest that drivers sit in a unique position that allows them to view every part of the F1 process. Drivers begin racing as children; they learn how to formulate driving tactics and acquire extensive technical knowledge from an early age. Former drivers may also appear more credible to members of their teams, and those ex-drivers may know, from their deep acquired experience, how to create an appropriate work environment for other team members.

Caution is advisable in the interpretation of any observational study in social science. It is sensible to recall that -- though we have here the entire longitudinal history of Formula One and not a snap-shot -- at this level of disaggregation any leader sub-samples necessarily become relatively small. Hence care is needed in the assessment of results. Despite such limitations, our findings have made it possible to consider the expert leader hypothesis in a new real-world setting; this iconic backdrop helps us to understand further its strengths, boundaries, and possible generalizability. We believe the issues merit further attention.

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Appendix 1

Summary of F1 performance: Twelve most successful teams 1950 – 2006*

Team	**Period of winning Grand Prix**	**Number of Grand Prix wins**	**Number of win periods**
Ferrari	1951 - 2006	186	7
McLaren	1968 - 2006	148	5
Williams	1979 - 2004	112	5
Lotus	1960 - 1987	79	4
Brabham	1964 - 1985	35	3
Renault (2 entries)	1979 - 1983; 2003 - 2006	33	3
Benetton	1986 - 1997	28	3
Tyrrell	1971 - 1983	23	2
BRM	1962 - 1972	17	3
Cooper	1958 - 1967	16	3
Alfa Romeo	1950 - 1951	10	1
Matra	1968 - 1969	10	1

*Table reproduced from Jenkins, 2010, p 901.

Appendix 2

Table 8: Clustered OLS regression results where the dependent variable is whether a car gains a podium position
[estimated for 2 years only where budget data are available: 2006 and 2008**]**
(clustered by year)

Explanatory variable	**Model 1 coefficient (robust standard error)**
DRIVER or MECHANIC	0.0987* (0.0075)
# CARS included	0.0081* (0.0003)
TEAM BUDGETS	0.0016** (0.000003)
Constant	-0.3782* (0.0091)
R^2	0.0728
N (Observations)	764
N (Clusters = Years)	2

* - significant at 0.05 level;
** - significant at 0.01 level

Notes: We have obtained estimates of budgets for the years of 2006 (http://en.wikipedia.org/wiki/Formula_One) and 2008 (http://www.f1fanatic.co.uk/2008/09/22/toyota-has-biggest-f1-budget-4456m/) and conducted OLS clustered OLS regression where we excluded individual leader and team effects but included obtained budget information. This budget information is not official figures (which are a part of each team's commercial secret and therefore are not obtainable) but expert estimates. Our results (presented above) show that even when the team effects are not included, having former driver or mechanic as the head of the team influences team performance more than the team budget. Particularly, while former driver or mechanic leader (rather than former manager or engineer) increases the propensity of team winning a podium position by 9.87%, higher budget increases the chances of winning a podium by only 0.16%. This suggests that our results remain stable even when we include budget estimates in our regressions.