EXPERT LEADERS IN A FAST-MOVING ENVIRONMENT*

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July 13, 2012

Abstract

This paper is an attempt to understand the effects of leaders on organizational performance. We argue for an 'expert leader' model of leadership. We differentiate between four kinds of leaders according to their level of inherent knowledge and industry experience. After controlling for confounding variables, teams led by leaders with extensive knowledge of the core business perform better than others. Our study collects and analyses 60 years of data from one of the world's most competitive high-technology sectors (Formula 1 competition) in which each organization's performance can be measured objectively. We show that the most successful team leaders in F1 motor racing are more likely to have started their careers as drivers and mechanics compared with leaders who were principally managers or engineers with degrees. There is a notable association between driving and later success as a leader. Within the sub-sample of former drivers, those with the longest driving careers go on to be the most successful leaders.

Keywords: expert leaders, leadership, organizational performance, high-tech, teams.
JEL classification: J33, M5, D22, O32, J24

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* We are grateful to Mark Goodall, Dan Hamermesh, Andrea Isoni, Lawrence Kahn, Andrew Oswald, Axel Wendorff and colleagues at an IZA brownbag for their helpful comments and suggestions.

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1. INTRODUCTION

There remains disagreement about the extent to which leaders can influence organizational performance. Management scholars have tried to separate CEO effects from industry or firm effects (Thomas 1988, Finkelstein and Hambrick, 1996, Waldman and Yammarino, 1999, Bertrand and Schoar, 2003, Jones and Olken 2005 Bennedsen, Perez-Gonzalez and Wolfenzon 2007). In this literature, the explanatory power from CEOs typically ranges from 4% (Thomas, 1988) to 15% (Wasserman et al., 2010) up to 30% (Mackey, 2008). Good management practices are strongly associated with performance and survival rates at the firm level (Bloom & Van Reenen, 2007; Bloom, Genakos, Martin & Sadun, 2010). However, scholars and practitioners disagree about the kind of knowledge and skills that a successful leader should possess. Many organizations consider leadership ability to be a key element of success and to require regular and significant investment (Noe et al., 1997; MacCall, 1998; London and Mone, 1999). According to a recent survey of 750 American companies, almost $11 billion has been spent on leadership training programs in 2010 (O'Leonard, 2011). Yet, despite being a substantial item of expenditure in corporate budgets, leadership training remains a controversial issue.

In this paper we concentrate on leaders' expertise in the core business activity of their organization. First, we identify the depth of knowledge and related expertise – what we call *inherent knowledge*. Second, we test whether a leader's inherent knowledge is correlated with organizational performance using data from a dynamic competitive industry. In earlier work a Theory of Expert Leadership was proposed to account for the positive impact of leaders' knowledge and expertise on organizational performance (Goodall 2009a; 2012). Empirically, using longitudinal data, it has been found that university presidents who were themselves top scholars seem to improve the later performance of their universities (Goodall 2009a,b). In another high-skill setting, Goodall, Kahn and Oswald (2011) found evidence that one predictor of a leader's success in year T was that person's level of attainment, in the underlying activity, in approximately year T-20; the study documents a correlation between brilliance as a basketball player and the (much later) winning percentage and playoff success of that person as a basketball coach.

Our study uses six decades of field data from the highly competitive industry of Formula 1 (henceforth, F1) World Constructors' Championship. In F1, each constructor team competes to win the Championship by entering two cars in consecutive races every year. The goal of a constructor team is to maximize the number of points gained in races. 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 down to tenth position). Constructor teams are relatively homogeneous and identical criteria are applied to measure their performance.

Leaders of constructor teams in F1 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 team, to control technical matters, and to make the majority of financial decisions. Leaders also oversee the selection of drivers who compete for their constructor teams and have a final say in making tactical decisions during each race.

Our dataset includes information on the performance of every car of each constructor team in every F1 race which has taken place between 1950 and 2011. We also collect background information about leaders of all F1 teams for the same time period. We identify four groups of leaders according to the level of their inherent knowledge and length of industry experience. Using econometric methods, which attempt to account for unobserved heterogeneity and allow for multiple control variables, we study constructor team performance and try to determine whether and to what extent leaders' competence in the core-business activity (such as driving), combined with industry experience (length of time), is predictive of team performance.

Our results suggest that leaders with inherent knowledge of the core-business activity combined with extensive industry experience are associated with better organizational outcomes. This study finds that the most successful team leaders in F1 motor racing are more likely to have started their careers as *drivers and mechanics* as compared with leaders who were principally *managers or engineers* (defined as those with engineering degrees).

We hypothesize that former drivers, in particular, become better leaders because they are familiar with all aspects of Formula 1. For example, we argue that, from an early age, driver-leaders develop technical knowledge about the underlying activity of Grand Prix racing; they acquire extensive experience in formulating driving tactics and combine it with a good understanding of mechanics; they are able to make decisions under time pressure and stress; finally, former drivers appear more credible to team members and are able to effectively communicate with any part of the racing team which, we suggest, influences team strategy. We show that among the sub-sample of drivers it is those with the longest driving careers who go on to make the best leaders.

This study attempts to contribute in various ways. First, we extend the literature which examines the impact of leadership ability on organizational performance (e.g., Bertrand, 2009; Kocher et al., 2010; Pogrebna et al., 2011). Our analysis is conducted using non-experimental data from the field, and our dataset, which contains thousands of observations, is one of the largest samples used to test the impact of leadership ability on performance. Our data enable us to measure exact organizational performance (over a 60 year period), and we have detailed measures of leader characteristics. Our paper also provides a theoretical contribution: we test the relevant implications of a 'theory of expert leadership'. Finally, this research potentially has some practical value because it can help form recommendations about the leader characteristics necessary to improve team or company performance.

The remainder of this paper is structured as follows. Section 2 summarizes the theory of expert leaders and formulates testable hypotheses. Section 3 introduces our dataset and provides basic statistics. In section 4 we present results of the econometric analysis. We discuss the implications of the findings in Section 5, and conclude in Section 6.

2. THEORY OF EXPERT LEADERSHIP AND TESTABLE HYPOTHESES

The theory of expert leadership (henceforth TEL) was developed to try to explain earlier empirical patterns (Goodall 2012). TEL can be represented by the following simple framework where f(…) is a function and expert leadership depends on three kinds of 'inputs':

$$EL = f\ (IK, IE, LC)$$

Expert leadership (EL) can be thought of as a function of: *inherent knowledge* (IK) defined as technical knowledge of the core-business activity that is acquired through education or practice, combined with high ability in the core-business activity; second, *industry experience* (IE) which equates to time and practice in the core-business industry; finally, *leadership capabilities* (LC) which includes management and leadership experience and training, acquired during a leader's earlier career, and his or her innate characteristics. TEL predicts that organizational performance is positively correlated with leaders' inherent knowledge, their industry experience, and also their leadership capabilities. Central to TEL is that each of these components is tied to the organization's core business.

TEL proposes that leaders should be specialists and experts. Interestingly, recent evidence suggests that CEOs in the top US public companies are more likely to be generalists; they have fewer technical qualifications (educational backgrounds in science, engineering or law) than their predecessors', but instead are more likely to have a business degree (Murphy & Zabojnik, 2006; Frydman 2007). In the context of F1, we can identify four types of leaders according to their competence and background: manager, driver, mechanic and engineer[1]. Leaders' capabilities (management and leadership skills and their innate characteristics) were not reported and thus are not included in the analysis.

Manager here refers to a leader with low or basic inherent knowledge and minimal industry experience. Often manager-leaders are successful businessmen or CEOs who move to F1 from a different (and often unrelated) industry. Managers do not 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. One of the more controversial examples of a manager is Flavio Briatore who started his career as a ski instructor and restaurant manager, then worked as a salesman, a broker and a manager in several positions in the Benetton clothing company. At the age of 38 he became a leader of Benetton F1 constructor team and was then exposed to the environment of competitive racing. Nevertheless, Briatore successfully managed Benetton F1 and Renault F1 constructor teams.

[1] All types are defined in relative terms: i.e., in relation to one another. Our econometric analysis allows us to account for individual effect of each leader. Therefore, individual heterogeneity is controlled for by econometric techniques.

Driver is assigned to leaders with high inherent knowledge and long industry experience. Driver-leaders have been involved in competitive racing (F1 and other racing competitions) as drivers from a very early age. Such leaders would often start as Go-kart racers either in their childhood or teenage years and then move to professional racing by their early 20s. Oftentimes drivers are familiar with the technical side of car making as well as with mechanical aspects of car repairing even though they do not complete degrees in mechanical engineering or a related field. For example, successful team leaders Jean Todt (Ferrari), Cesare Fiorio (Ferrari, Ligier, Minardi), and Tom Walkinshaw (Tom Walkinshaw Racing) were involved in competitive racing in their teens and were driving cars professionally by their early 20s. Red Bull Racing has won both the Constructors' Championships and the Drivers' Championships in 2010 and 2011. The Red Bull team leader is Christian Horner, who was also previously a racing driver.

Mechanic is a leader with medium inherent knowledge and average industry experience. Mechanics have practical technical experience in car making and mechanical repair but have not driven competitively and have not obtained a degree in mechanical engineering or a related field. Leaders of this type may start being involved in car mechanics in their teens by working at a family or friends' workshop. However, despite the fact that they gain mechanical experience from a very early age, mechanics typically become exposed to a competitive racing environment later than drivers. For example, Henri Julien (Automobiles Gonfaronnaises Sportives) started working as a mechanic in his 20s but built his first racing car only in his mid-30s.

Finally, *engineer* here depicts a leader with low inherent knowledge of the core business activity and short industry experience. Engineers are, of course, skilled professionals; but as a category in this study they are defined more abstractly, namely, as those with degrees in mechanical engineering. Due to the fact that they devote several years of their life to obtaining education, they tend to become exposed to the competitive racing environment relatively late compared with drivers and mechanics. For example, Tony Purnell (Jaguar, Red Bull) had a relatively long academic career in engineering before moving to F1 racing sport at the age of 44.

Figure 1 presents the four leader types in a TEL matrix of expert knowledge and industry-related experience in Formula 1. Using the testable implications of TEL and four types described above, we can formulate the following hypotheses:

Hypothesis 1: Constructor teams led by principals with high inherent knowledge will outperform teams headed by leaders with low inherent knowledge.

Hypothesis 2: Constructor teams led by principals with high industry experience will outperform teams headed by leaders with low industry experience.

Next we test these hypotheses using econometric methodology.

[INSERT Figure 1 HERE]

3. DATA AND BASIC STATISTICS

Our dataset covers the performance of every car in every Grand Prix race in the 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.[2] We collected data on: the starting and final position of all cars that participated in each race; the constructor teams represented; their leaders' names, personal information and background; each driver's personal information and background; and

[2] We do not consider qualifying races or practice sessions conducted before each Grand Prix race.

information about the race circuit. 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.[3]

Our dataset has several important advantages. First, it covers a highly competitive industry where decisions are made instantaneously. Furthermore, the excitement, time pressure and fast speed of competition can be observed live on major TV channels. In other words, the decisions of team leaders and the conditions of the competition are often observable in real time (and dialogue between team leader and driver often audible).

Second, in contrast to many industries where agents have heterogeneous size and output, F1 constructor teams have relatively homogeneous size, capabilities and output. These characteristics make it a natural industry for our study. The goal of an F1 team is to score as many Championship points as possible. The higher is the position of the car in the final grid, the more points are awarded to its constructor team. Their common motivation means that relative comparison of teams' performance can be more exact than in settings where different companies make different products. This setting offers an unusual opportunity to compare organizations in a precise way.

Third, the core work-teams in F1 are relatively small, which allows a natural background against which to begin to try to understand the influence of leaders.

[3] 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) – an F1 governing organization, and sometimes on Wikipedia.

Finally, our starting dataset on car race entries contains the entire population of data rather than a statistical sample and constitutes one of the largest datasets on leaders examined in the literature to this date.

Even though we have collected the entire population of entries into F1 World Constructors' Championship, to test our theoretical hypotheses, we had to drop several observations. All team executives listed by the team as 'principal of the racing team' or 'team principal' are identified as team leaders. Several teams in F1 history were managed by several executives, i.e., by collective leaders. Since the focus of this paper is on the effects of core business knowledge and industry experience of individual leaders, we decided to exclude these collective leaders from consideration (29 collective leaders, 1,351 car entries). In several cases we were unable to identify team leaders and locate their biographical information. This happened in two cases: either the information about a particular leader of a well-known team was not available for a certain period of time, or several cars which did not represent any particular constructor team entered races.[4] For these few teams/entries we were unable to find the identity of leaders as well as their biographies. These observations were excluded (460 car entries). Overall, we have dropped 1,811 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.

Our dataset has several other important features. First, in each racing season the number of constructor teams in the Championship differs. For example, while 21 teams competed in 1960, only 12 were in the Championship in 2011. The decline in the number of competing teams is primarily due to the high cost associated with the sport which has increased over the years. If in

[4] These primarily refer to the entries into Indianapolis Grand Prix races in 1950s and 1960s.

1950s and 1960s amateur mechanics could enter their self-made cars into races, current race car manufacturing requires long-term R&D investments and a lot of expensive testing, affordable only to a narrow circle of sponsors. The average annual budget of an F1 constructor team is approximately $173 million.[5] 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).

Each F1 race is a Grand Prix and the number of races conducted annually has increased from 7 in 1950 up 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 change sometimes from one season to the next[6]. This does not interfere with our data because each change applies to every team in each championship. In our econometric analysis of the data we control for the season of the competition and therefore take into account the heterogeneity which may result from changes from season to season.

The majority of F1 constructor teams' profits come from advertising revenue.[7] A higher finishing position, primarily a podium (first to third), means higher brand exposure and, as a result, more sponsorship money for the next season. In each championship, team performance is measured by the number of points attained. Throughout the history of F1 Constructor Championship, the points system has been subject to significant changes. Table 1 summarizes the different championship point systems which have existed in F1 between 1950 and 2011.

[INSERT Table 1 HERE]

[5] This estimate is provided by the Formula Money website www.formulamoney.com
[6] Jenkins (2010) provides a detailed summary of these changes and their impact on F1 technology.
[7] See Formula Money website www.formulamoney.com for more details.

To have a universal measure of performance in our econometric analysis, we use the relative final positions of cars in the race (instead of the number of obtained points). Since most points are awarded to winning teams as well as teams that obtained podium positions (positions 1, 2 and 3), we primarily concentrate on winners of the race and podium winners for each race.

The biographical information on leaders that we collected allows us to separate them into four groups identified in the previous section: managers, drivers, mechanics and engineers. In our dataset, all leaders were male. The basic statistics of the dataset are provided in Table 2a. According to our classification, leaders are fairly evenly distributed across the four background groups. More precisely, there are 42 (29.8%) managers, 35 (24.8%) drivers, 31 (22.0%) mechanics, and 33 (23.4%) engineers.

[INSERT Table 2a HERE]

Despite a possibility of ambiguity in leaders' classification, such cases are rare. For example, only 6 leaders out of the 141 have both driver's and mechanic's experience. However, several leaders had either multi-level expert knowledge or several industry experiences. In this case, we assigned types according to the following criteria. If the leader had multi-level expert knowledge he was assigned to the type according the highest level of knowledge he obtained. For example, if a leader worked as a mechanic and then obtained a degree in mechanical engineering or a related field, he was classified as an engineer. In cases where the leader could be assigned to several types characterized by similar levels of expert knowledge, he was classified according to his primary area of activities. For example, if a leader was building his own cars and then drove these self-made cars in local amateur races, he was classified as a mechanic. If a leader had some mechanical experience but then moved to a professional racing team as a driver, he was classified as a driver.

The summary statistics in Table 2a show that between 1950 and 2011 the highest numbers of cars were entered by constructor teams led by mechanics (7,456), which, as we will discuss later, is explained by an over-representation of mechanics in the 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).

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 gaining a podium.

The mean values in Columns 4 and 5 of Table 2a 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 2a and Figure 2.

[INSERT Figure 2 HERE]

Overall, while the raw patterns reported in Table 2a are of interest, they should not be interpreted in too literal a way. The data provide a preliminary summary without accounting for any confounding variables. These variables potentially have an important impact on teams' performance and, therefore, interact with leaders' types.

4. ECONOMETRIC ANALYSIS AND RESULTS

In this section we use econometric analysis to test theoretical hypotheses identified in Section 2. 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).

Apart from our main interest, we explore the impact of several control variables on performance and check whether inserting a certain control changes the results. Particularly, circuit (due to specific shape or likely weather conditions), year of competition (due to imposed rules and regulations) and number of cars in each race (due to competitive pressures) might have an impact on the team result. Furthermore, some teams might perform consistently better than others. For example, it might be that Ferrari or McLaren constructor teams often outperform others not because they have successful leaders but because they have a long history of competing in F1 and traditionally have better facilities, more sponsorship money and highly experienced human resources. Our regression analysis controls for factors which may influence performance. Explanatory variables used in our regression analysis are summarized in Table 2b.

[INSERT Table 2b HERE]

We begin with a preliminary analysis of the data by dividing into two: those leader-types with medium to high inherent knowledge and industry experience (drivers and mechanics), and those with lower knowledge and experience (managers and engineers). Table 3a reports an OLS regression model without control variables. Table 3a 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 gained a podium in a race ($\pi_i = 1$) or did not gain a podium in the race ($\pi_i = 0$).

[INSERT Table 3a HERE]

Column 1 of Table 3 reports an OLS regression model in which a dummy variable is entered for leaders classified as drivers or mechanics. Since π_i is a simple binary variable, the estimated coefficients of this dummy, in the first column of Table 3a, give estimates of the effects of drivers or mechanics as compared with managers or engineers on the propensity to gain a podium position. In each row, the base category is that of manager or mechanic.

In Table 3a the coefficient on driver or mechanic in Column 1 is 0.066 (with a t-statistic of 12.56, which implies that the null hypothesis of a zero coefficient can be rejected at 0.001 level). Because the mean probability of securing a podium position is approximately 0.14, a coefficient of 0.066 implies that the probability is raised ceteris paribus by six percentage points to approximately 0.20 when we add in the extra effect of having a former driver or mechanic as team leader.

The remaining columns of Table 3a report simple specifications in which we add a number of control variables to our basic regression analysis. In particular, we control for the circuit where the race is taking place, the year of competition, constructor team[8] a particular car represents as well as for the total number of cars that participate in the race.

Column 2 of Table 3a reveals that when we control for the circuit in which the race takes place, drivers and mechanics compared with managers and engineers are associated with higher propensity of gaining 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 taking part in each race, our results remain stable. Overall, results in Table 3a show that drivers and mechanics are associated with better organizational performance compared with managers and engineers.

Results of the basic analysis reported in Table 3a 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. Our 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. In order to take into account individual unobserved heterogeneity at the level of each leader, to account for the binary nature of the dependent variable (gaining or not gaining a podium position) and to make use of

[8] Jenkins (2010) provides a comprehensive review of the possible impact of constructor's effects on wins. For a brief summary, see the Appendix.

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).[9]

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

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

where $x_1 \dots x_n$ are explanatory variables; $\beta_0,\ \beta_1 \dots \beta_n$ 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 3b.

[INSERT Table 3b HERE]

Table 3b shows that results of the multilevel probit regression are qualitatively similar to the results of the simple OLS models presented in Table 3a. 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 unobserved heterogeneity of leaders.

Although sub-samples inevitably become small, we can make an attempt to understand the effect of each leader type (managers, drivers, mechanics and engineers) separately. As above, we first conduct a simple analysis and then estimate more complex models with unobserved individual heterogeneity at the level of each individual leader. Table 4a reports an OLS regression model without control variables in which a separate dummy variable is entered for each type of leader (manager, driver, mechanic, and engineer). As with Table 3a, π_i (dependent

[9] Estimations are conducted using GLLAMM for STATA.

variable equal to 1 if a car gains a podium position and 0 otherwise) is a simple binary variable, the estimated coefficients of the dummies which represent leader types in the first column of Table 4a give estimates of the individual effects for the type of team leader. In each row, the base category against which all leader types are compared is that of manager.[10]

[INSERT Table 4a HERE]

In Table 4a the coefficient on driver in Column 1 is 0.044 (with a t-statistic of 5.07, which implies that the null hypothesis of a zero coefficient can be rejected at any conventional confidence level). Because the mean probability of securing a podium position is approximately 0.14, a coefficient of 0.044 implies that the probability is raised ceteris paribus by four percentage points to just under 0.18 when we add in the extra effect of having a former driver as team leader. A similar, though slightly smaller, advantage exists when mechanics are team leaders (coefficient of 0.043; t-statistic 6.10, $p<0.001$). However, a significantly negative effect is generated by engineer-leaders. Here the coefficient in the first column of Table 4a is -0.042 with a t statistic of -5.28 ($p<0.001$).

It should be emphasized that these patterns in Column 1 of Table 4a are simply associations in the data with no adjustment for possible confounding variables. Nevertheless, they are consistent with the view that drivers and mechanics are more effective as leaders than managers who in turn are more effective than engineers. In the analysis reported below we probe the data

[10] Econometrically, any explanatory variable representing leaders' types can be chosen as the base category, but the choice of manager allows coefficients to be read off in a simple way since managers do not have much technical training and short industry experience. Hence, leaders of other types are compared to managers. To check the robustness of our results we have run additional estimations with other variables as base categories and received very similar results. Results of these estimations can be obtained from authors upon request.

to see whether this finding changes when other independent variables are included (in broad outline they do not, but in detail they do).

The remaining columns of Table 4a report simple specifications in which only one leader variable at a time is included. These should be seen as ways of describing the patterns in the data, not as ideal specifications of the kind we would propose. These later columns of Table 4 effectively vary the omitted base category.

Column 2 of Table 4a reveals that managers, compared with the three other kinds of leaders, are slightly negatively associated with gaining a top-three finishing place: the t statistic is -2.97 ($p<0.05$). By contrast, having the team led by a driver or a mechanic, in Columns 3 and 4 respectively of Table 4a, is associated with a considerably raised probability of finishing the race either first, second or third. In Column 3 of Table 4a, the coefficient on drivers, compared to the combined effect of all other leader types, is 0.034 (t-statistic 4.78, $p<0.001$) and the coefficient on mechanics is 0.047 (t-statistic 9.02, $p<0.001$). This probability of getting a podium position, however, goes negative when we examine the coefficient for engineers in Column 4. Overall, results in Table 4a show that drivers and mechanics are associated with better organizational performance compared with managers and engineers.

Table 4b reports results of the multilevel probit regression given by equation (1). As with Table 4a, Table 4b shows that drivers and mechanics are associated with higher propensity to attain podium positions than managers and engineers. This result is robust and consistent with our theoretical prediction.

[INSERT Table 4b HERE]

To consider the relative impact of leaders' types on team performance taking into account several control variables, we also use a probit model. Table 5a reports the results of the probit estimations. In these estimations we include several confounding variables (shown in Table 2b). 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).

[INSERT Table 5a HERE]

In Table 5a, the probit model in Column 1 controls only for each Grand Prix circuit (there are 71 circuits in our dataset). Compared to managers, teams headed by drivers are statistically more likely to attain 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, $p<0.001$). As with the earlier results, in Table 5a 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 5a 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 5a. 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 R^2 which rises in Table 5a from approximately 0.02 in Columns 1 and 2, to 0.14 after the addition of team fixed-effects.

Column 3 of Table 5a 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 remains 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 5a, 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 5b.

In Table 5b, 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 effect sizes of four different categories.

[INSERT Table 5b HERE]

Although it is sensible to be cautious, Tables 4a, 4b, 5a and 5b allow us to summarize several results. The most important finding, one that confirms our hypotheses in Section 2, is that constructor teams headed by leaders with high inherent knowledge and longer industry experience seem to perform better than leaders with low to average inherent knowledge and industry experience. Constructor teams led by drivers and mechanics are more successful than teams headed by managers and engineers. The findings in Tables 3a-5b are consistent with the theoretical hypotheses and suggest particularly that former drivers are statistically more likely to lead their constructor teams to podium positions and wins. To explore whether improved performance of these teams is associated with leaders who have extensive industry experience, we conduct several additional regressions. Results from our time-in-industry estimations are reported in Tables 6a-7b.

Here we address the question: does the amount of driving experience make a difference? We identify those leaders who have <u>ever</u> 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). According to our hypotheses based on the theory of expert leadership, these 45 principals have the longest relevant experience among all types of leaders considered in our analysis. To explore whether such experience might be the main determining factor of a team's success, we conduct several econometric estimations.

Table 6a and Table 6b show that, according to the OLS estimation, the length of leaders' previous experience (in competitive driving) has a robust positive statistically significant effect on both number of wins and podiums gained by the constructor team. The positive effect of leaders' previous industry experience (via competitive driving) can be seen in Column 1, of Table 6a, which presents the results with no controls; the coefficient is 0.006 (t-statistic 2.11, $p<0.05$). Column 2 includes a dummy variable for the race circuit (coefficient 0.008; t-statistic

2.57, $p<0.01$) which does not alter the result. Similarly, in Columns 3 to 5 as we add the confounding variables of year of race, team constructors, and the number of cars that qualified in each race, the effect of previous experience in competitive driving on podiums increases; the coefficients consistently rise to 0.016 (t-statistic 2.38, $p<0.02$) in Column 5.

[INSERT Table 6a and Table 6b HERE]

At this point in our analysis, to give a feel for the size of effects, it is helpful to consider what happens when a leader has 10 years of experience instead of zero years. This is associated with an extra 0.16 on the dependent variable, which is large. It translates into a 16 percentage points higher probability of the leader's team gaining a podium position – this is after controlling for circuit dummies, year dummies, constructor dummies and number of cars qualified. 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 (see Table 2a).

Table 6b shows that a leader's previous industry experience (via competitive driving) also has a positive effect on this leader's team's winning chances. The coefficient again rises across the columns. Column 1 summarizes an estimation with no control variables and reports a coefficient of 0.002 which is only on the margin of significance (t-statistic 1.73, $p<0.09$). Column 5 includes four control variables for circuit, year of race, constructor team and number of cars qualified. In Column 5 of Table 6b the coefficient is 0.007 (t-statistic 2.02, $p<0.05$). Ten years of competitive racing experience by a leader is likely to improve a team's winning success by approximately 7 percentage points, which is 2 points above the average win frequency of 0.05 (reported in Table 2a).

To account for the possible impact of unobserved heterogeneity of leaders on performance, we conduct 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:

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

where $\boldsymbol{X1_i^t}$ is the leader's years of experience as a competitive driver in the past and $\boldsymbol{X2_i^t} \dots \boldsymbol{XM_i^t}$ are explanatory variables described in 2b, $\boldsymbol{\beta_1} \dots \boldsymbol{\beta_M}$ 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:

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

The log-likelihood function (2) is approximated using the Newton-Raphson method.[11] Results of the random intercept logit regressions estimated with different number of explanatory variables are reported in Table 7a (where the dependent variable is obtaining a podium position) and Table 7b (where the dependent variable is winning a race).

[INSERT Table 7a and Table 7b HERE]

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

Interestingly, in both Tables 7a and 7b 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 gaining a podium position when we do not control for the constructor team. 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.

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 or achieve 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 race or gaining a podium position at home as compared with abroad.[12]

5. DISCUSSION

In this paper we have focused on leader characteristics in longitudinal F1 data to try to identify which kinds of leaders are beneficial to performance. Identification is a problem in the investigation of leadership and organizational performance (Antonakis, Bendahan, Jacquart, & Lalive 2010). Nevertheless, extensive resources go into hiring, remunerating, and, when

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

necessary, firing institutional heads; thus, it continues to be an important topic for research. The team principal in F1 is responsible for the day-to-day running of the team. 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 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. The role of team leader will differ as has been suggested; however, some of the decisions made by principals include choosing drivers, having the final word on technical issues such as how the car is set up, pit strategy, which gearbox or engine is used, and they may also be involved with financial decision-making, for example, about sponsorship or team wages.

In this study our important findings point to, first, the strong association between driving and leading: time spent as a racing driver, in any competitive class, generates strong results for those who become team leaders, as compared especially with leaders who were principally managers or engineers (with degrees). Second, the more years spent as a racing driver, the better the results for those who later become team leaders. Why might this be? In this section we address this question and raise a number of possible explanations with reference to the Theory of Expert Leadership (TEL).

The central proposition in the TEL model presented in Section 2 (Goodall, 2009a, 2012) is that leaders with inherent knowledge of the core-business activity, combined with extensive industry experience, and leadership capabilities, are associated with better organizational outcomes. Inherent knowledge is acquired through practice, training or education, combined with high ability in the core-business activity (Goodall 2012). Our results support this proposition. Team leaders who spent most years racing, arguably the most successful drivers, secured, as leaders, the best results for their teams. How exactly team leaders might affect performance is an empirical question; however, a number of possible mechanisms are raised in TEL (Goodall, 2009a, 2012).

Evidence from the psychology literature on intuition and expertise, suggests that individuals who have extensive domain experience and practice have greater intuitive knowledge, and make more effective decisions (Klein 1993, 2003; Dane and Pratt, 2007) which, it is argued, results in enhanced performance (Ericsson, Krampe, & Tesch-Romer, 1993). F1 team principals who had long driving careers, may have gone on to become exceptional leaders because their own career preferences and priorities continue to be aligned with the requirements of the core business of F1 Championships. Also, at an early age, driver-leaders develop technical knowledge about the underlying activity of Grand Prix racing; they acquire extensive experience in formulating driving tactics, and are able to make decisions under time pressure and stress. The suggestion here is that when leader characteristics align with core business activity, it shapes organizational strategy. Having specialized knowledge about racing might help a leader to create superior, knowledge-based strategies. In addition, they may be better able to effectively communicate strategy to any part of the team.

Inherent knowledge is not a proxy for management and leadership ability. As might be presumed, leaders should be selected based on their management skills as well as technical expertise (Mumford, 2000). However, the evidence in this study shows that being a manager alone is not sufficient. Managers did not perform well as F1 team leaders. Many former drivers have worked in the field of racing for years, and those who have become principals may have acquired their leadership skills as they rose through the ranks.

An important part of the theory behind the promotion of expert leaders is the requirement that not only should heads be knowledgeable about the core business, but they should also be highly competent in the core activity (Goodall, 2009b, Goodall, et. al, 2011). TEL predicts that it will be easier for a leader to be an effective quality-enforcer if he or she has first met the approximate standard that is to be imposed.

Former drivers may also, because of their proven track record, command more respect; they may be viewed as intrinsically credible since they have 'walked-the-walk'. Credibility, it is argued, legitimizes leaders' authority (Bass, 1985; Bennis & Nanus, 1985; Kouzes & Posner, 2003). Having been 'one of them' may also signal that a driver-leader understands the culture and value system, incentives and motivations of their F1 team colleagues. Thus, we might expect driver-leaders to create the right work environment. In addition, they may act as role models within the team, and be more likely to coax high performance. Importantly, their presence may help to attract other talented personnel; and, finally, a function of successful managers in high pressure, high performance workplaces may be to manage the egos of the workers involved. In the context of North American professional basketball, Goodall et al. (2011) argue that having been a former top basketball player helps those who become coaches to better manage the egos of their top players.

The propositions raised in this section to explain why and how expert leaders – particularly driver-leaders – may improve performance need to be tested in further settings. Nevertheless, it is hoped that the theory of expert leaders, further developed in this paper, may help to frame some of the questions for future research.

6. CONCLUSION

This paper attempts to advance our knowledge about the influence of leaders on organizational performance. Leaders are not randomly assigned to organizations, so caution is advisable in the interpretation of any observational study. Here we have focused on leader characteristics in longitudinal data to try to identify which kinds of leaders are most successful. Our study collects and uses six decades of field data from the highly competitive industry of Formula 1 World Constructors' Championship. The dataset includes information on every car of each constructor team in every F1 race between 1950 and 2011. We also collect background information on leaders of all F1 constructor teams for the same time period.

We identify four groups of leaders according to their background characteristics: drivers, managers, mechanics, or engineers (with degrees). It is sensible to recall that -- even though we have here the whole history of Formula One and not a sample -- at this level of disaggregation the sub-samples become small. Hence particular care is needed in the assessment of such results. Figure 2 and Tables 3a and 3b give grouped results at a slightly higher level of aggregation, namely, a division into drivers-and-mechanics compared to managers-and-engineers. That two-way breakdown can be seen as an approximate split between those with high and low expertise.

Our motivation is to try to understand how necessary it is for leaders to have in-depth industry knowledge and experience. We test our hypotheses that successful leaders are those with inherent knowledge of, and high ability in, the core business of their organization, coupled with long industry experience. Using econometric methods, to account for heterogeneity and multiple control variables, we compare teams' performance and determine whether and to what extent leaders' competence in the core-business activity (driving), combined with industry experience (length of time), affect team performance.

This study's results suggest that in the highly skilled industry of Formula 1 it is driver-leaders and former mechanics who have greater potential to improve team performance -- specifically, to reach podium positions and wins -- than other types of leaders. We find a strong association between driving and leading, and the more years of experience as a driver the better are the organizational outcomes. These results hold when we control for the constructor team, year of competition, number of cars in each race, and the circuits where Grand Prix take place.

We draw from a Theory of Expert Leadership (TEL) to try to explain why the most successful team leaders in F1 motor racing are more likely to have started their careers as drivers or mechanics. We suggest that former drivers may make the best leaders because they are familiar with all aspects of the activity. From an early age, driver-leaders develop technical knowledge about the underlying activity of Grand Prix racing; they acquire extensive experience in formulating driving tactics, and are able to make decisions under time pressure and stress. This inherent knowledge and industry expertise may, we suggest, inform organizational strategy when drivers become principals. We also argue that former drivers may appear more credible to their F1 team colleagues, which extends their influence. Finally, because of a shared value system between the team and leader, driver-leaders may create a more appropriate work environment for the team.

Two case studies of F1 constructors' teams illustrate our results. The first is that of Ferrari, who have competed in F1 since it began in 1950. Figure 3 shows the whole history of Ferrari's success. The black bars represent years when the team was headed by former drivers. Jean Todt (a former driver) was team principal from 1995 to 2007. During this period Ferrari reached the peak of its performance. In 1990-91, Cesare Fiorio, who also had competitive driving experience, was team head. Overall, the average podiums achieved by Ferrari under non-drivers' leadership is equal to 0.29 and under drivers 0.52. This difference is significant according to Wilcoxon Mann-Whitney test ($p<0.0001$).

A second and more recent example is a team currently located at the top of the grid in the Formula 1 constructor championship – Red Bull Racing. The Red Bull team is led by a former racing driver, Christian Horner. In the last two seasons (2010, 2011) they have won two consecutive constructor championships (see Figure 4), and Sebastian Vettel (who is currently the youngest double-champion in the history of Formula 1), has won two driver championships. The fact that Red Bull has progressed from the bottom of the championship grid to becoming one of the leading Formula 1 teams between 2005 and 2011 suggests that TEL may have a broader appeal and potentially predict the dynamics of progress for teams at the bottom of the championship grid.

[INSERT Figure 3 and Figure 4 HERE]

Leadership can be a loaded topic and it is sometimes hard for observers to suspend a natural desire to rely on anecdotes. Based on the evidence in this paper, we argue (cautiously) here for an 'expert leader' model of effective leadership. These important issues merit future research.

Figure 1

Theory of expert leadership (TEL) matrix: Inherent knowledge and industry-related experience in Formula 1 team leaders

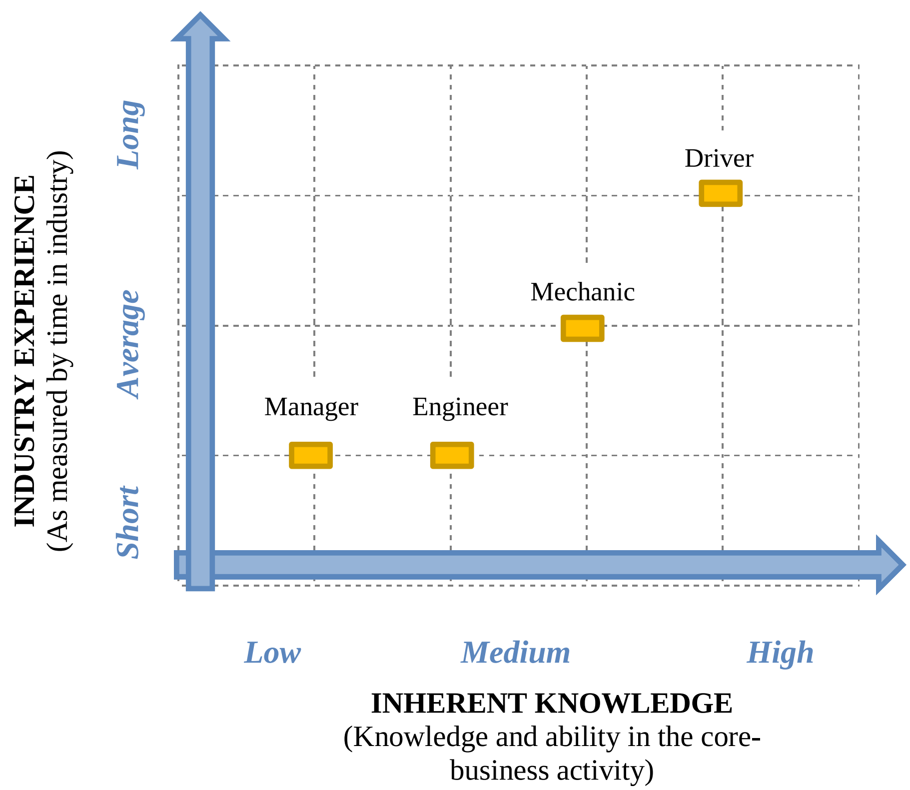


Table 1
The relationship between F1 Champion points and the final position of cars

	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

Table 2a
Summary statistics of Formula 1 World Constructors' Championship 1950-2011

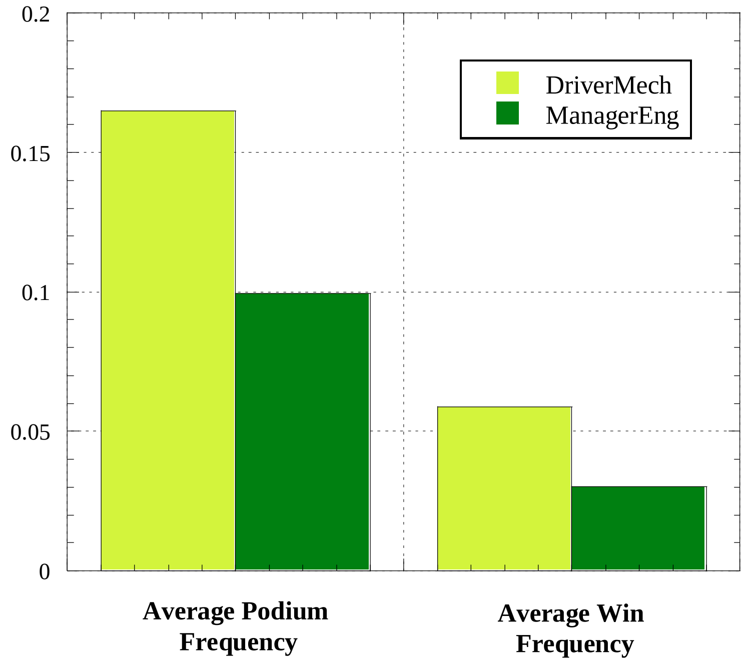
Leaders' type	Number of leaders	Number of cars	Average podium frequency	Average win frequency	Average pole frequency	Average fastest lap frequency
Managers	42	3,498	0.12	0.03	0.03	0.04
Drivers	35	2,779	0.17	0.07	0.07	0.06
Mechanics	31	7,456	0.16	0.06	0.05	0.06
Engineers	33	3,992	0.08	0.03	0.03	0.03
Total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

Table 2b
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.

Figure 2
Average podium frequency (1-3) and win frequency of F1 leaders who were drivers or mechanics (DriverMech) compared with those 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).

Table 3a

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. Standard errors are in parentheses.

Table 3b

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   Standard errors are in parentheses.

Table 4a
Regression equations where the dependent variable is whether a car gains 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)
MANAGER		-0.019** (0.006)			
DRIVER	0.044*** (0.009)		0.034*** (0.007)		
MECHANIC	0.043*** (0.007)			0.047*** (0.005)	
ENGINEER	-0.042*** (0.008)				-0.074*** (0.006)
CIRCUIT dummies included	NO	NO	NO	NO	NO
YEAR dummies included	NO	NO	NO	NO	NO
TEAM dummies included	NO	NO	NO	NO	NO
# *CARS* included	NO	NO	NO	NO	NO
Adjusted R^2	0.0102	0.0004	0.0012	0.0045	0.0080
N (Observations)	17725	17725	17725	17725	17725
N (Leaders)	141	141	141	141	141

Standard errors are in parentheses. ** - significant at 0.01 level;
*** - significant at 0.001 level

Table 4b
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 (marginal effect)	Model 2 coefficient (marginal effect)	Model 3 coefficient (marginal effect	Model 4 coefficient (marginal effect)	Model 5 coefficient (marginal effect)
MANAGER	-	-0.157*** (0.040)			
DRIVER	0.194*** (0.068)		0.118** (0.039)		
MECHANIC	0.242*** (0.066)			0.671*** (0.034)	
ENGINEER	-0.138 (0.073)				-0.362*** (0.045)
Individual leader's effect st. deviation (st. error)	0.575 (0.006)	0.592 (0.006)	0.642 (0.008)	0.591 (0.006)	0.584 (0.021)
CIRCUIT dummies included	NO	NO	NO	NO	NO
YEAR dummies included	NO	NO	NO	NO	NO
TEAM dummies included	NO	NO	NO	NO	NO
# CARS included	NO	NO	NO	NO	NO
Log-likelihood (LL)	-5997.32	-5959.35	-6013.35	-5982.92	-6000.54
N (Observations)	17725	17725	17725	17725	17725
N (Leaders)	141	141	141	141	141

Standard errors are in parentheses.
** - significant at 0.01 level
*** - significant at 0.001 level

Table 5a

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

Standard errors are in parentheses. *** - significant at 0.001 level

Table 5b
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

Standard errors are in parentheses. * - significant at 0.05 level
** - significant at 0.01 level
*** - significant at 0.001 level

Table 6a

Regression equations where the dependent variable is whether a car gains a podium position -- estimated by OLS model -- in the subsample of leaders who have had competitive driving experience[1]

Explanatory variable	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 5 coefficient (robust standard error)
Leader's years of experience as a competitive driver in the past	0.006* (0.003)	0.008** (0.003)	0.008** (0.003)	0.016* (0.007)	0.016* (0.007)
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	0.0104	0.0288	0.0325	0.2232	0.2233
N (Observations)	6061	6061	6061	6061	6061
N (Leaders)	45	45	45	45	45

* - significant at 0.05 level   Standard errors are in parentheses.

** - significant at 0.01 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 1950-2011. 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.

Table 6b
Regression equations where the dependent variable is whether a car wins a race -- estimated by OLS model -- in the subsample of leaders who have had competitive driving experience[1]

Explanatory variable	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 5 coefficient (robust standard error)
Leader's years of experience as a competitive driver in the past	0.002† (0.001)	0.003* (0.001)	0.003* (0.001)	0.007* (0.003)	0.007* (0.003)
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	0.0041	0.0163	0.0174	0.1169	0.1170
N (Observations)	6061	6061	6061	6061	6061
N (Leaders)	45	45	45	45	45

† - significant at 0.10 level   Standard errors are in parentheses.
* - significant at 0.05 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 1950-2011. 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.

Table 7a

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)	-1617.8844	-1596.0317	-1599.1844	-1494.9343	-1494.9332
N (Observations)	6061	6061	6061	6061	6061
N (Leaders)	45	45	45	45	45

*** - significant at 0.001 level Standard errors are in parentheses.

[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 1950-2011. 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.

Table 7b

Regression equations where the dependent variable is whether a car wins a race -- estimated by the 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	0.039** (0.015)	0.042* (0.019)	0.040*** (0.018)	0.109* (0.048)	0.108* (0.056)
Leader in each season individual effect st. deviation (st. error)	2.553 (1.327)	2.577 (1.353)	2.581 (1.324)	1.050 (0.189)	1.043 (0.185)
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)	-797.1258	-779.1452	-775.1342	-723.3454	-723.0263
N (Observations)	6061	6061	6061	6061	6061
N (Leaders)	45	45	45	45	45

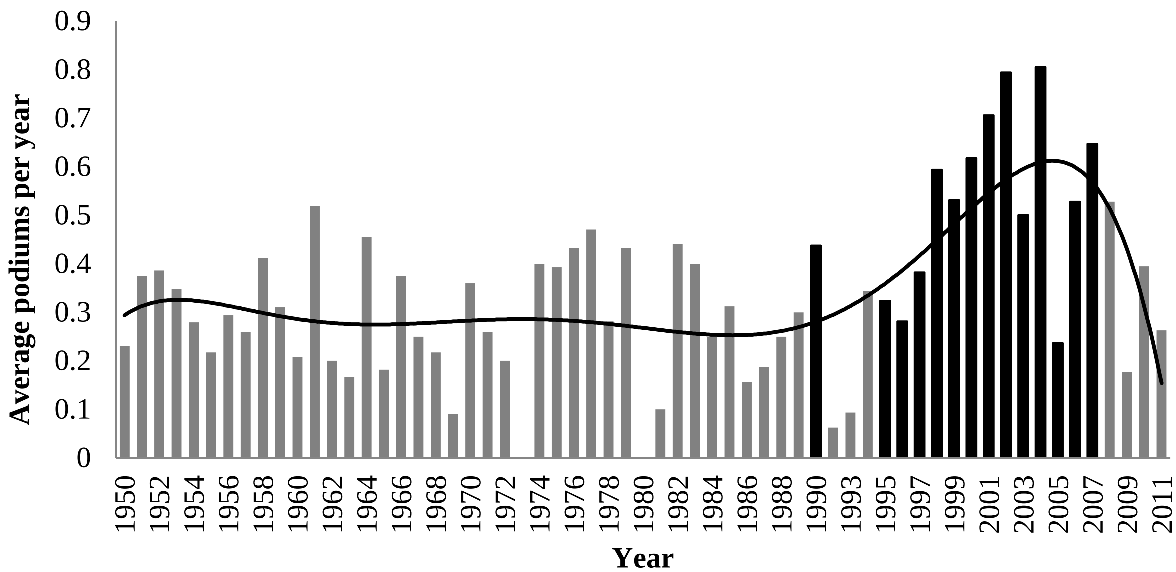
* - significant at 0.05 level   Standard errors are in parentheses.

** - significant at 0.01 level

***- significant at 0.001 level

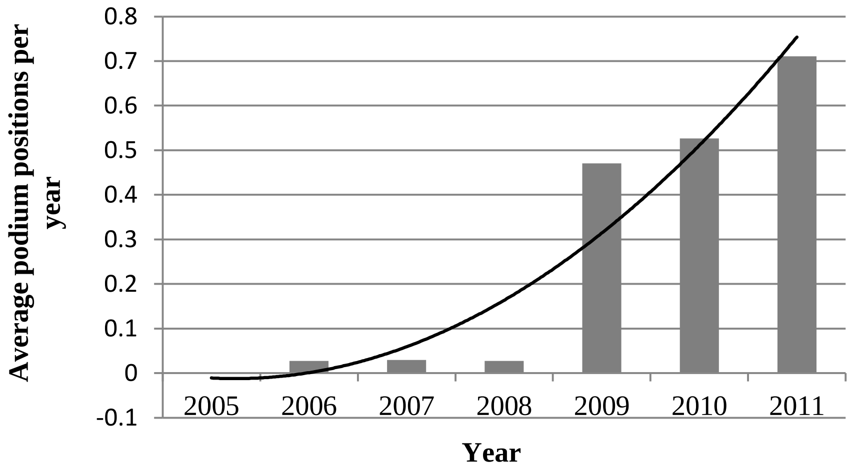
[1] The data include 45 leaders out of 141 (33%) who have entered 6,061 cars in 803 out of 858 races in F1 competitions between 1950-2011. These are leaders who have ever had a competitive driving experience. Out of them, 35 are classified as drivers, 7 as mechanics, 2 as managers, and 1 as engineer.

Figure 3
Expert leaders' influence at Ferrari Formula 1 Team from 1950 to 2011
(Average podium positions*)



*Black bars show years when the team was headed by former drivers.

Figure 4
The recent success of the Red Bull Team under a driver-leader from 2005 to 2011
(Average podium positions*)



*This figure shows how under the leadership of former driver Christian Horner (2005-2011) Red Bull has progressed

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APPENDIX

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.