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The Speedy Road to Success: Knowledge Overlap in R&D Teams

Annamaria Conti
Georgia Institute of Technology
College of Management
Annamaria.Conti@mgt.gatech.edu

Karin Hoisl
Ludwig-Maximilians-University
Munich School of Management
hoisl@bwl.lmu.de

Abstract

The importance of teamwork in the production of R&D-intensive output has been widely acknowledged and understanding its mechanisms has become crucial. This study focuses on a particular aspect of the organization of R&D-intensive teams, the level of knowledge overlap of its members. We analyze the relevant trade-off a firm needs to solve when choosing the optimal level of knowledge overlap for its R&D team. In fact, on the one hand, a large knowledge overlap is often associated with low coordination costs. On the other hand, to the extent that production in R&D-intensive sectors consists of problem solving, a large overlap is then associated with a low probability that the solution to these problems lies within the team knowledge set. We show that, under certain conditions, there exists a level of knowledge overlap which maximizes the present discounted value generated from the innovations produced by the team, over its life horizon. We test this prediction using a novel dataset on R&D top management teams in Formula 1. Having controlled for a large number of factors, we find an inverted u-shaped relation between the value produced by the team and its degree of knowledge overlap.

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1 Introduction

The importance of teamwork in the production of R&D intensive output has been widely acknowledged in the economic literature. Adams et al. (2005), Wuchty et al. (2007), and Jones (2009) find that more and more research output is produced in teams, whose size has increased over time. Given the increased importance of teamwork, understanding the mechanisms that govern its organization has become crucial.

Previous studies have examined the optimal size of teams as a trade-off between specialization gains and coordination costs (Becker and Murphy, 1992). Marschak and Radner (1972), Cremer (1993), and Prat (2002) have elaborated a theoretical analysis on the optimal organization of teams. Zenger and Lawrence (1989), Hambrick and Mason (1984), O'Reilly and Flatt (1989), Finkelstein and Hambrick (1990), Lazear (1998), Hoxby (2000), Leonard and Levine (2003), Hamilton et al. (2003), Hamilton et al. (2004), Bandiera et al. (2005), and Conti et al. (2011) have empirically analyzed the relation between certain aspects of a team's organization and productivity.

We examine a setting in which an R&D firm manager has to determine the level of knowledge overlap in a team by hiring team members with a given knowledge background, acquired through past experience. In this setting, we investigate the relevant tradeoff the manager needs to solve. In fact, on the one hand, knowledge overlap is often associated with low coordination costs among team members. On the other hand, to the extent that production in R&D-intensive sectors consists of problem solving (Garicano and Rossi-Hansberg, 2003; Garicano and Hubbard, 2005), then, for given knowledge sets of the team members, the higher the team knowledge overlap, the smaller the size of the team knowledge set, and the lower the number of problems whose solution falls within this set. We test the prediction of the model using a novel dataset on top management R&D teams in Formula 1. To our knowledge, this paper is the first to consider the impact of team knowledge overlap on team performance. It is also one of the few that looks at the organization of teams in R&D intensive firms.

R&D top management teams are deemed to play a very important role in the production of a firm's innovations (O'Reilly and Flatt, 1989). The mechanisms governing the organization of these teams are the same as those governing R&D teams in general, with two exceptions. The first is that R&D top management teams are likely to make a greater number of decisions per unit of time. The second is that their decisions are likely to have a greater impact on team performance than those made by other team members, given that they have to organize the work of the other team members and coordinate their tasks (Hambrick and Mason, 1984; Finkelstein and Hambrick, 1990). Therefore, it is reasonable to believe that the trade-off we mentioned is even more relevant in the context of R&D top management teams than in that of R&D teams in general.

Our model shows that there exists an optimal level of knowledge overlap in an R&D team which maximizes the presented discounted value of a firm and, thus, resolves the trade-off described above. This value is that generated from the innovations produced by a team, over its life cycle. The model draws from insights by Marschak and Radner (1972), Cremer (1993), and Prat (2002) who find that a firm's choice regarding whether a team should be homogeneous or heterogeneous depends on whether the team members' actions are complements or substitutes in the firm payoff. Our model differs in that rather than considering the firm problem as a dichotomous choice between homogeneous and heterogeneous teams, it models the payoff of a firm as a continuous function of the level of knowledge overlap within a team. The latter affects negatively both, the coordination costs the team members have to incur and the value of an innovation.

In the empirical analysis we use data on top management R&D teams in Formula 1, which operated over the period 1993-2008. Formula 1 is a highly innovative industry, where car constructors have to promptly react to rapid technological advancements and highly dynamic regulatory environments and face an important threat of imitation by competitors. In this context, top management teams play a fundamental role in organizing and supervising the work of the R&D department. These teams are typically made of three key engineers, the technical director, the chief designer, and the chief aerodynamicist.

Using a multiplicity of sources, we collected detailed information on the experience of R&D top management teams in Formula 1 as well as in other industries or race series, team members' past performance, and demographic characteristics. We also gathered information on the team principal, who, while not a member of the top management R&D team, is in a position of influencing the activity of this team. In fact he is responsible for making strategic decisions such as, for instance, hiring the team members and the drivers.

We approximate the value generated from the innovations of a Formula 1 R&D top management team by the percentage deviation of a car's qualifying time from that of the fastest car, at race i. This is because innovations are produced having as an objective the improvement of a race car's performance, of which speed is a fundamental component. We relate our measure to the degree of knowledge overlap in the R&D top management team. Although we are interested in the value generated over the life-cycle of a team and on its relation with the team level of knowledge overlap, we estimate our models at the level of the race, in order to control for factors such as weather conditions or characteristics of a race track, which might affect the performance of a car but are not related to the performance of the R&D top management team. We then approximate the total value produced by a team during its life-cycle by the average car performance over the team life-cycle. The approximations we made are reasonable if we consider that innovations in Formula 1 have a high rate of obsolescence. In fact, car constructors need to continuously innovate in order to cope with the threat of imitation and with frequent changes in the regulatory environment. Therefore, even though a car's performance depends also on past innovations, the contribution to a car's performance in the present period, by the current R&D top management team, is likely to be larger than past contributions.

We construct two measures of knowledge overlap based on information we collected on the areas of experience of the R&D top management teams. Our main finding is that, having controlled for a large number of factors, the performance of a car increases in the level of knowledge overlap of the R&D top management team, it reaches a maximum for values of knowledge overlap which fall between the 60th and the 70th percentile, in the case of the first overlap measure, and between the 70th and the 80th percentile, in the case of the first overlap measure, and declines for larger values of knowledge overlap. Moreover, the concave relationship we found is robust to estimating an instrumental variable model which corrects for a potential omitted variable bias. In this case, though, the optimal level of knowledge overlap is reached for lower levels of the indexes. Given the way we measure a team's life-cycle value, the inverted u-shape relation we found between the performance of a car at a given race and the level of team knowledge overlap carries over to the relationship between overlap and the value the team generates during its life-cycle. This result is in line with our theoretical prediction which suggests that, beyond a threshold value of team knowledge overlap, the forgone payoff from having a diverse team solving the problems related to an R&D project prevails over the reduction in coordination costs.

By emphasizing the importance of coordination among team members, our work contributes to a stream of literature which analyzes the conditions under which multi-divisional forms (M-forms) and unitary forms (U-forms) are optimal for R&D intensive firms (Maskin et al., 2000; Qian et al., 2006). In contrast to these studies, ours focuses on the level of knowledge overlap of a top management team and, thus, does not consider how the activities of a top management team *and* the rest of the R&D team should be organized. Moreover, our study contributes to a stream of the literature which has studied the mechanisms that enhance team productivity. Zenger and Lawrence (1989), Leonard and Levine (2003) have investigated the relationship between diversity in demographic factors and team productivity. Hamilton et al. (2003), Hamilton et al. (2004) have looked at the relationship between the distribution of team members' abilities and productivity. Conti et al. (2011) have studied the role of team task specialization in enhancing team productivity. Hoxby (2000) and Bandiera et al. (2005) have analyzed the role of incentives and peer effects on team productivity. Finally, Hambrick and Mason (1984), Finkelstein and Hambrick (1990), and O'Reilly and Flatt (1989) have looked at some aspects of top management teams, such as demographic characteristics and tenure, and related them to various measures of performance. Our focus is on R&D top management teams that are knowledge-intensive and on the optimal combination of their members' knowledge sets.

The remainder of the paper is organized as follows. Section 2 presents a simple model of knowledge overlap. Section 3 describes the data and presents the empirical results. Section 4 concludes.

2 Knowledge overlap and the relevant tradeoff

In this section we describe the relevant tradeoff an R&D firm manager faces when forming an R&D team of a given size. The firm manager needs to choose among potential candidates with a certain background of experience. Candidates' past experience determines the size as well as the composition of their knowledge sets. Since our focus is on the composition of the team members' knowledge set, we make the assumption that all candidates have the same knowledge set's size. The managers' selection of the team members therefore determines their level of knowledge overlap and, with it, the size of the team knowledge set. In making her selection the manager faces the following tradeoff. On the one hand choosing team members with similar past experiences, and, thus, with a high overlap in their knowledge sets, reduces the initial costs the team members have to incur in order to learn how to coordinate their activities. On the other hand, to the extent that production in R&D-intensive sectors consists of problem solving (Garicano and Rossi-Hansberg, 2003; Garicano and Hubbard, 2005), for a given size of the team members' knowledge sets, the higher the team knowledge overlap, the smaller the size of the team knowledge set, and the lower the number of problems whose solution falls within this set. In a very simple model, we show that, under certain conditions, there exists an optimal level of knowledge overlap among the members of an R&D team which takes into account the two terms of the trade-off just presented. This model is built upon the fundamental insights from the theory of optimal firm organization (Aghion and Tirole, 1995; Maskin et al., 2000; Qian et al., 2006). Similar to Qian et al. (2006), we derive the present discounted value of an R&D firm as a function of our key parameters. We then show that there exists an optimal level of team knowledge overlap which maximizes the firm's value function.

2.1 Setup

We begin by characterizing an R&D team and the choice a firm manager has to make relative to the team level of knowledge overlap. AN R&D team lives for n periods and in every period it works on an innovation project which differs from that in the previous period. The goal of an innovation project is to produce an innovation. Similarly to Garicano and Rossi-Hansberg (2006) and Garicano and Hubbard (2005), innovation production consists of solving a set of problems which are ensued from a project. An innovation is more valuable the more problems a team is able to solve. Specifically we define the value of an innovation by the number of problems, P, that a team can solve. The maximum number of problems which are generated by a project is finite and equal to N. We assume that the number of problems the team members can solve is a subset of the number of problems which are generated by an R&D project. We relate P to the level of knowledge overlap within a team. The logic here is that, for given knowledge sets of the team members, the smaller their overlap, the larger the team knowledge set and the greater the number of problems which can find a solution within the team knowledge set. Thus, P is a decreasing function of the level of knowledge overlap, S, which implies that $\frac{dP(S)}{dS} < 0$. Moreover, the loss in terms of a reduced P, which results from an increment in the level of knowledge overlap, becomes larger as the level of knowledge overlap increases. Thus, $\frac{d^2P(S)}{dS^2} < 0$. When working together to solve problems, the members of a team need to coordinate their tasks. Learning task coordination requires a one-time fixed cost, C, on the part of team members. We model this cost as a decreasing function of the level of knowledge overlap within the team, S, which implies that $\frac{dC(S)}{dS} < 0$. In fact, the greater knowledge overlap, the greater the reciprocal understanding of the team members' tasks, and the lower the coordination costs. We posit that the reduction in C, due to an increment in S, becomes smaller as S increases. Hence, $\frac{d^2C(S)}{dS^2} > 0$.

Even if P problems have been solved at the end of a period, there is still a likelihood that the innovation produced does not meet the needs of its final users. We define $\lambda \in (0, 1)$ as the probability that the innovation produced meets the needs of its final users, in which case a firm increments its initial payoff by P. If the innovation produced does not meet the needs of its final users, then the firm receives a payoff of zero.

2.2 Firm payoff at stage zero

We begin by defining the payoff of a firm at stage i, where i is the stage at which i projects have been successfully implemented. At this stage, the current period payoff is $(i+1)P(S)$ with a successful new project. If the new project is not successful, then the firm still enjoys a payoff of $iP(S)$, which is the sum of the payoffs from past successful projects. The recursive formula for the firm's payoff at stage i, in terms of the net present value V_i, is:

$$V_i = -C(S) + \lambda[(i+1)P(S) + \delta V_{i+1}^{UF}] + (1-\lambda)(iP(S) + \delta V_i)$$

Where $\delta < 1$ is the discount factor. Let $a = \frac{1}{1-(1-\lambda)\delta}$. We have that:

$$\begin{aligned} V_i &= a[-C(S) + \lambda(i+1)P(S) + \lambda\delta V_{i+1} + (1-\lambda)iP(S)] \\ &= -aC(S) + a\lambda P(S) + aiP(S) + a\lambda\delta V_{i+1} \end{aligned}$$

Solving recursively, we obtain the payoff at stage zero:

$$V_0 = -aC(S)\sum_{i=0}^{n}(a\lambda\delta)^i + a\lambda P(S)\sum_{i=0}^{n}(a\lambda\delta)^i + aP(S)\sum_{i=0}^{n} i(a\lambda\delta)^i$$

Using the relation $\sum_{i=0}^{n} x^i = \frac{1-x^{n+1}}{1-x}$, we simplify the expression above and obtain:

$$V_0 = [\lambda P(S) - C(S)]\frac{a[1-(a\lambda\delta)^{n+1}]}{1-a\lambda\delta} + aP(S)\sum_{i=0}^{n} i(a\lambda\delta)^i \tag{1}$$

Result 1. *There exists an optimal value of S, S^*, which maximizes a firm's payoff at stage zero and such that for values of S greater than S^* the firm's payoff is smaller.*

The optimal value of S, S^*, is found by computing the first derivative of $V_0(S)$ with respect to S and equalizing it to zero. Because $\frac{d^2C(S)}{dS^2} > 0$, $\frac{d^2p(S)}{dS^2} < 0$, and $0 < a\lambda\delta < 1$, S^* satisfies the second-order optimizing condition: $\frac{\partial^2 V_0(S)}{\partial S^2} < 0$.

3 Empirical Estimation

We use Formula 1 data and relate the value that is generated from the innovations produced by Formula 1 R&D top management teams to the level of knowledge overlap within these teams. Formula 1 motorsport is a car race series (like American IndyCar series) governed by the FIA (the Fédération Internationale de l'Automobile).

Formula 1 motorsport is a highly innovative industry. Both rapid advancement in technology and highly dynamic regulatory environments require prompt action by the car constructors. The latter have to engage in continuous innovation in order to improve the speed as well as the reliability of their cars. Moreover, due to a high visibility of the technology on the race track, constructors find it difficult to protect their innovations from imitation. In addition, Formula 1 motorsport is characterized by high labor turnover rates as well as strong dependence on a network of suppliers, both of which favor informal dissemination of knowledge and, with that, imitation (Jenkins, 2004; Mastromarco and Runkel, 2009). Because imitation erodes the constructors' first-mover advantage from adopting innovations, to keep their advantage, they need to maintain high the rate at which they produce innovations.

Even though Formula 1 R&D teams consist of a large number of engineers, we will focus on the organization of the top management of these teams. This is usually composed of three key engineers: the technical director, the chief designer and the chief aerodynamicist. These engineers are responsible for making the final decisions relative to the production of innovations and their implementation on a race car.

3.1 Formula 1 constructors and organization of R&D top management teams

In Formula 1, a number of race constructors (e.g., Ferrari, McLaren, or Williams) design, manufacture and race highly specialized single-seater, open wheel race-cars. Constructors are medium sized companies located in Europe, mainly in the region around Oxford in the UK. They operate budgets up to 415 million USD. Currently, Formula 1 is a global industry, generating 4.4 billion USD revenues per year. Grand Prix are held at different locations around the world on purpose-built race tracks (circuits) or public roads. Each constructor is allowed to compete with two cars. At the end of each season, the drivers and the constructors that scored the most points are awarded the Drivers' and Constructors' Championship title by the FIA (Sylt and Reid 2010; Aston and Williams 1996; Jenkins 1994).

According to Article 6.3 of the FIA Formula 1 Sporting Regulations, constructors have to build the chassis of their race cars. This requirement distinguishes Formula 1 from other race series like, for instance, American IndyCar Series, which allows constructors to buy chassis[1].

Figure 1 shows the organizational structure of a Formula 1 constructor. Generally, the organizational structure differs between so-called works teams and pure chassis constructors. The first are fully integrated constructors owned by car manufacturers, such as Ferrari, Toyota or Renault, that design and manufacture the chassis of a car as well as its engine. The second, owned by private individuals or investment consortia, only design and manufacture the chassis. In the case of a works team, the chairman of the Formula 1 constructor is also a chairman for the car manufacturer (e.g., Luca di Montezemolo for Ferrari, who is also chairman for Fiat, the parent company of Ferrari). In the case of privately owned teams, the chairman is the co-owner of the constructor (e.g., Dietrich Mateschitz for Red Bull Racing).

⟨ Insert Figure 1 about here ⟩

[1] See http://www.fia.com/en-GB/sport/regulations/Pages/InternationalSportingCode.aspx, accessed on September 14, 2011.

A Formula 1 R&D team consists of between 15 and 18 engineers typically headed by three key engineers: the technical director, the chief designer, and the chief aerodynamicist.[2] There are few cases in which a team is made of only two key engineers. These cases are mainly confined to the early years when the chief aerodynamicist was not always included in a top management team. It is only in the 1980s that top management teams begun systematically studying the aerodynamic properties of a car, that is after Colin Chapman had made the path breaking invention of the ground effect[3]. This, subsequently, led to the creation of the role of the chief aerodynamicist, which then, progressively, became part of the top management team. There are also cases in which a team is made of four key engineers. This tends to occur either when a constructor wants to ensure a smooth transition from a chief designer to another or if it estimates that the tasks of a chief designer are more efficiently performed if assigned to two employees instead of one. This last case is more frequent for large constructors. Bruno Mauduit, former team leader of Renault Formula 1, describes the organization of an R&D team as a pyramidal structure on top of which stands the management team consisting of the technical director, the head of R&D (referred to as the chief designer), and the chief aerodynamicist (Mauduit and Midler, 2000). These key engineers have to work closely together to make sure that the different parts of a car (chassis, engine, aerodynamics, tyres, etc.) fit together and that R&D efforts result in a competitive car. To give a flavor of the importance of teamwork at the top of the pyramid, Jenkins (2011) ascribes the lack of competitiveness of the 2011 Ferrari car to a lack of coordination within its top management team. The importance of team work is also acknowledged by Ross Brawn, former technical director at Ferrari. Jenkins (2011) reports the following statement by Ross Brawn back in 2004: "if we had an innovation here it's the fact that we combine the engine and the chassis together as one whole, but we apply that principle to all areas of the car with the electronics, the engine, the chassis, the aerodynamics, the structure, it

[2]In case of a works team, the R&D top management team also contains a chief engine designer. Since the focus of our analysis is the construction of the chassis of a car and not engine construction and since both areas require different types of experience, chief engine designers have not been taken into account. However, to capture differences between the two types of constructors, our regression analysis contains a dummy variable controlling for works teams.

[3]At the end of the 1970s, Colin Chapman, a very successful race car (Lotus 87) constructor, made the path breaking invention of the ground effect, i.e. the opposite of aerodynamic lift, sucking the car to the track, allowing to corner at a much higher speed. This innovation enabled Lotus to win the Formula One World Championship in 1978 (Jenkins and Floyd, 2001). See http://www.autoevolution.com/news/ground-effects-in-formula-1-6717.html, accessed on October 5, 2011.

all had to be a whole, there was no point in having one area very strong and the other area weak."[4]

In what follows we describe the main tasks of the R&D top management team members: the technical director, the chief designer, and the chief aerodynamicist.

The *technical director* (TD) is the head of R&D division and is generally responsible for the design, development and deployment of race cars. Additionally, he is also responsible for performance and reliability of the cars. His duty consists in ensuring the overall functioning of the cars, and specifically in bringing together chassis, engine, drivers, tyres, and other car components. Moreover, he also reviews actual technical and regulatory developments. The chief designer and the chief aerodynamicist report to the technical director.

The *chief designer* (CD) is responsible for the basic layout of the race car, i.e. for transforming single components with potentially conflicting requirements like chassis, suspension, gearbox, engine, aerodynamics, transmission, and brakes into a competitive car. Moreover, he is also responsible for choosing the materials that are used for building a car.

The *chief aerodynamicist* (CA) is the head of the aerodynamics division. Aerodynamics has to create downforce in order to keep the car onto the track and to increase cornering speed. At the same time aerodynamics has to minimize air drag that would slow the car down. To fulfill this difficult task, aerodynamicists use full-sized wind tunnels and enormous computing power for simulation purposes[5].

As shown in Figure 1, on top of the R&D management team stands the *team principal* (e.g. Jean Todt for Ferrari or Christian Horner for Red Bull Racing). When the constructor is a works team, the team principal is typically one of the top employees of the mother company (e.g., Fiat S.p.A. in case of Ferrari). In case the team is privately owned, the team principal is usually either a former driver, or a former engineer or a manager and, typically, also holds the position of the chairman (e.g., Jackie Stewart for Stewart Grand Prix). The team principal can be broadly defined

[4]See http://f1professor.wordpress.com/page/2/, accessed on October 5, 2011.
[5]See http://auto.howstuffworks.com/auto-racing/motorsports/formula-one5.htm, accessed on August 12, 2011.

as the person in charge of the day-to-day routine of the constructor. He is typically responsible for contracting sponsors and suppliers, as well as for recruiting drivers and engineers. He also determines the wages of the employees, takes care of financial matters and of the factory at the home base. Furthermore, even if the team principal is not responsible for the construction of the car or aerodynamics, he has the final say in all strategy matters[6]. In this analysis we focus on role of the team principal as a bridge between the R&D top management team and the drivers of the race cars.

Finally, as shown in Figure 1, in addition to the R&D team, Formula 1 constructors employ race and test teams (responsible for testing new components of the car), manufacturing, marketing, public relations and hospitality, as well as logistics departments.

We constructed our dataset by combining different electronic and paper-based sources. We extracted data on the composition of top management teams and on the cars that Formula 1 drivers had driven during our sample period from "motorsportarchiv"[7]. Moreover, we gathered the names of the team principals from the Formula 1 yearbooks[8]. We obtained data on qualifying classifications from the electronic database "motorsport total"[9]. We then supplemented these data with information on the biographies of the team principals and the key engineers. We gathered this information through extensive web search. Finally, we obtained information on the budgets of the Formula 1 constructors from Formula 1 yearbooks, for the years 1993 to 2006[10], and from Formula 1 financial reports, for the years 2007 and 2008[11].

The resulting dataset includes 88 Formula 1 R&D top management teams which operated during 1993-2008. In this period, our teams built a total of 141 race cars, with an average of 1.8 cars per team. For these cars, we observe 2359 qualifying outcomes for the respective Formula 1 World Championship races (*Grand Prix*). R&D top management teams were employed by 13 Formula

[6]See http://auto.howstuffworks.com/auto-racing/motorsports/formula-one5.htm, http://uk.answers.yahoo.com/question/index?qid=20110108115948AA3jL30, accessed on August 12, 2011.
[7]See, http://www.motorsportarchiv.de, accessed on August 12, 2011.
[8]See "Grand Prix live miterlebt", edited by Willy Knupp.
[9]See http://www.motorsport-total.com/, accessed on August 12, 2011.
[10]See "Grand Prix live miterlebt", edited by Willy Knupp.
[11]See "Formula Money", edited by Christian Sylt and Caroline Reid.

1 constructors and managed by 32 team principals. Their average duration was 1.8 years, the minimum being 1 year and the maximum 7 years.

3.2 Econometric Methodology

In our theory, we have related the value generated from the innovations that are produced by an R&D team over its life cycle to the level of knowledge overlap within the team. In our empirical analysis, we first estimate the value generated by a team from working on an innovation project, which we defined in the theoretical model as the number of problems solved during a project and which met the needs of an innovation's final users. We then approximate the total value produced by a team during its life-cycle by the average value produced by the team over its life-cycle.

Since in the case of Formula 1, innovations are aimed at improving the performance of race cars, of which speed is a fundamental component, we approximate the value produced by a team during an innovation project by the percentage deviation of a car's qualifying time from that of the fastest car during a pre-race knockout session (*Qualifying*), which takes place one day before the race. During this session each driver has a number of trials (*flying laps*) to determine the grid position of his car during the race. Estimating the contribution of an R&D top management team at the race level allows us to netting out the effect of factors, other than the innovations produced by the R&D top management team, that might effect the qualifying time of a car.

We then approximate the total value produced by a team during its life-cycle by the car's qualifying score averaged over the team life-cycle. This approximation is a reasonable one given that innovations tend to have a high rate of obsolescence (Bosworth, 1978; Schott, 1978; Pakes and Schankerman, 1984). It is even more reasonable in the case of Formula 1 innovations, because they are subject to an important threat of imitation and Formula 1 constructors have to cope with frequent changes in the regulatory environment. Therefore, even though a car's performance depends also on innovations produced in the past, the contribution to a car's performance, in the present period, by the current R&D top management team, ought to be larger than past contributions. To give an idea of the obsolescence rate of innovations in Formula 1, McLaren has recently announced that only about 6% of its Formula 1 car, which scored second in the Formula 1 Championship of 2011, will remain unchanged in 2012, even though the rules hardly changed.[12].

Our dependent variable of interest, *Performance*, is thus defined as:

$$Performance = (-1) * \frac{q_i - q_{pole}}{q_{pole}} \tag{2}$$

where q_{pole} refers to the qualifying time of the fastest car and q_i to the qualifying time of driver i. To facilitate interpretation of the dependent variable, we have multiplied the ratio by (-1). Hence, higher values of the index indicate better performance. We believe that using the qualifying time of a car during the pre-race knockout session gives a better indication of the innovation value produced by an R&D top management team than using the time at the actual race because during the knockout session competing cars are not allowed to block each other. Hence, their qualifying time is independent of drivers' strategic considerations or duels on the race track and, for this reason, it is more suitable to reflect the contribution of a top management R&D team. Each constructor is allowed to race with two cars per race (*Grand Prix*). Due to the fact that the performance of a race car during qualifying can be influenced by accidents, driving errors, or the driver's physical conditions -all of which are independent of the technical achievements of the R&D teams- we only consider the qualifying performance of the fastest of the two cars.

We relate *Performance* to the level of knowledge overlap in the team. As we discussed in the previous section, our assumption - based on Formula 1 literature and information from Formula 1 related websites - is that team members' knowledge is cumulated through past experiences. Therefore, the level of knowledge overlap in a team is reflected by the level of overlap in the team members' past experiences. By examining the curricula of the team members we identified five major areas in which Formula 1 key engineers had worked prior to joining their current teams. These areas are: industries other than Formula 1, CART sport, Formulas other than Formula 1

[12] $http://www.formel1.de/de/3260/McLaren\%3A+Hohes+Entwicklungstempo+\%C3\%BCber+den+Winter/newsID/1671674$. Accessed on November 21st, 2011

(e.g., F2, GP2, F3000), Formula 1 constructors other than the current one, and race car building for non-commercial events. We are confident that these areas are relevant to the performance of Formula 1 R&D key engineers based on extensive evidence we gathered from engineers' biographies, interviews, and from the job descriptions of the positions of R&D engineers posted by constructors on their websites. To cite a few examples, Rory Byrne, a star engineer at Benetton F1 and Ferrari F1, prior to joining Formula 1 worked as chief chemist at a polymer manufacturing plant. He then set up a company importing performance car parts, called Auto Drag and Speed Den. He cites these two past experiences as being instrumental for his current position[13]. Moreover, Niccolo Petrucci, chief aerodynamicist at Toro Rosso, mentioned that in setting the aerodynamic properties of the car Toro Rosso STR 6, which raced during the season 2011, he drew from experience collected at Ferrari F1 in 1992.[14]. McLaren F1 indicates on its web page that they look for engineers, designers, and mechanics that have "previous experience in other motorsport companies ... normally at a lower level"[15]. Finally, Adrian Newey, star designer at March F1, Williams F1, McLaren F1, and Red Bull F1, cites that experience in race car building for non-commercial events was instrumental in learning how to improve a car's performance[16]. Table 1 shows the relative distribution of the five areas of experience across top management engineers in an R&D team. We distinguish between teams of two, three, or four members. It clearly emerges that experience in industries other than Formula 1, in Formulas other than Formula 1, or with Formula 1 constructors other than the current one occurs more frequently than experience in CART sport or in race car building for non-commercial events.

⟨ Insert Table 1 about here ⟩

Based on the fields of experience we had identified we built two indexes of knowledge overlap, which we use alternatively in our regressions. To build the first index, *Overlap I*, we assigned a score of 1 if all team members had experience in any of the five areas, a value of 0.5 if two of the three

[13]See http://www.grandprix.com/ft/ft00223.html, accessed on September 14, 2011.
[14]See http://www.f1technical.net/news/16631, accessed on September 9, 2011.
[15]See http://www.mclaren-jobs.com, accessed on September 14, 2011.
[16]See http://www.grandprix.com/gpe/cref-newadr.html, accessed on December 14, 2011.

team members had experience in that area, and a value of zero if none of the team members had experience in that area. In case a the team principal had hired two chief designers, and therefore the team consisted of four members, we summed the areas of experience of the two chief designers and compared them to the fields of the other team members. Finally, in the case in which the team was made of two members, we assigned the score of one if both team members had experience in any of the five areas and zero otherwise. Once assigned the scores, we summed them across the five fields. Due to the difficulty of retrieving information on the number of years the team members had worked in each area, we refrain from weighting our scores using this information. The resulting index varies between 0 and 3, higher values indicating a large overlap of team members' experiences and, thus, a large team knowledge overlap. The upper bar chart of Figure 2 illustrates the density of this index. As shown, about 64 percent of the teams have a value of the index varying between 0.5 and 1.5, 20 percent of them have a value of zero, while about 17 percent have a value equal or above two. The second index, *Overlap II*, is a Herfindahl Index which is defined as the sum, across areas of experience, of the square of the share of team members who have experience in area j. This index could take values between 0 and 1, greater values indicating a higher level of experience overlap. The mean value of the index is 0.24, with a minimum of 0.04 and a maximum of 0.65. The distribution of this index is shown at the bottom of Figure 2. In order to take into account the possibility that there is an inverted u-shape relationship between our measures of overlap and the performance of a car, we include in our regressions the square term of the two overlap measures.

⟨ Insert Figure 2 about here ⟩

In our regressions, we control for additional factors which might affect the performance of a car. The first set of controls is aimed at capturing some characteristics of the team principal. Specifically, we construct three dummy variables indicating whether the team principal is a former race engineer, or a former race driver (in Formula 1 or in other race series), or has a purely managerial background. These dummies are labeled as *TP former engineer*, *TP former driver*, and *TP employed manager*, respectively. Being responsible for hiring the drivers and the R&D top management engineers, a team principal has to determine their optimal match. Hence, he has a potential for influencing the probability that the innovations generated by the team members meet the requirements of its final users, e.g., the drivers. This corresponds to the parameter λ in our theory. Our prior is that a team principal, who has first-hand experience, either as an engineer or as a driver, can better gauge the optimal match between engineers and drivers than a team principal who has only held managerial positions in the past.

Additionally, we control for the size of an R&D top management team using three dummies. The first is equal to one if a team is made of four members, the second is equal to one if the team is made of three members, and finally the third is one if the team consists of two members. These dummies are labeled as *Team_size_2*, *Team_size_3*, and *Team_size_4*. We also control for the breadth of experience of the team members, by summing the areas of experience of each member. We denote this variable as *Experience breadth*. We include a variable, *Former productivity team*, which is defined as the share of team members who have won a championship title in a race series different than Formula 1 and it is meant to control for the quality of the team members. Moreover, we use the sum of the number of years each team member has worked in Formula 1 to control for the R&D top management team's experience in Formula 1. We also include a squared term to account for the possibility that team members' experience in Formula 1 has a non-linear effect on the performance of a car. We denote the variables as *Experience in F1* and *Experience in F1 sqr.* Following Hamilton et al. (2003) and Hamilton et al. (2004), we control for team tenure, i.e. the number of Formula 1 seasons during which a team had remained unchanged. The rationale here is that the longer the team members work together, the lower the costs of coordination they incur. We denote this variable as *Team tenure*. Again we include a squared term to take into account a possible inverted u-shaped relationship between *Team tenure* and the performance of a car. Finally, we include the average age of the team members, which we denote as *Average age* to control for some demographic aspects of the team.

We include three dummy variables indicating whether a Formula 1 constructor had kept both drivers, only one driver, or none of the drivers, relative to the previous season. The innovations generated and then implemented in car have to be tailored to the characteristics of the drivers. Learning these characteristics entails a cost for the engineers, which is of course lower if the drivers do not change from one season to another. The cost reduction ensued from working with the same drivers has been widely acknowledged in Formula 1. As an example, Matchett (2002) reports that the policy by Benetton F1 of frequently substituting its drivers had caused discontent among its engineers in the 1990s. We label the three dummies as *Same drivers*, *One driver the same*, and *All new drivers*. Using a similar logic, we include an indicator variable, *Race of the season*, which takes the value of one if a car is competing in the first race of the season, two if it is competing in the second race, three for the third, and four for the fourth race of the season, etc. In fact, there are likely to be economies of learning the greater the experience the R&D top management team cumulates over a season. The variable also controls for different types of innovations. In particular, innovations at the beginning of a Formula 1 season are typically radical but may well become incremental over the season.

To distinguish between works teams, which build both the cars' chassis and the engines (e.g., Ferrari or Toyota), and pure chassis constructors (e.g., McLaren or Williams), which only build the chassis, we construct a dummy variable, *Works team*, that takes the value of one if a team is a works team and zero otherwise. We also include controls that capture some characteristics of a car's constructor. The first variable, *WC constructor*, controls for the past performance of the constructor. It is a dummy that takes the value of one if the constructor was awarded the title of "Constructor World Champion" in any of the prior 5 years and zero otherwise. The second variable, *Constructor's budget*, measures the annual budget, expressed in real terms[17], that is available to constructors for paying drivers, engineers and support staff, the chassis (R&D, material, wind tunnel), tyres, fuel, transportation, logistics, and public relations. For comparability reasons, we use budgets without engine costs. We include a squared term to account for the possibility that the relationship between the budget available to a constructor and the performance of a car has an inverted u-shape form. Finally, we measure the quality of a driver with a dummy, *WC driver*, that

[17]The consumer price indexes (CPI) were obtained from the U.S. Department of Labor, Bureau of Labor Statistics, Washington D.C., see ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt; accessed August 30, 2011.

is equal to one if the driver won the Driver Word Championship and zero otherwise.

To control for the characteristics of a race track, we use a dummy, *City track*, that is equal to one if the race track is a city track (ordinary street like, e.g., Monaco) and zero in case of a purpose built race track (i.e., circuit specifically designed for Formula 1 or other race series). Whether a car performs better on purpose built race tracks or on city tracks depends, among others, on its characteristics. Typically, cars with a higher top speed or cars with better aerodynamic properties, i.e. with more downforce, perform better on purpose built race tracks. The performance of a car is likely to be affected by the weather conditions during a race, as well. Particularly, since we expect rain to negatively affect the performance of a car, we include a dummy variable, *Rainy_weather*, which takes the value of one in case of rainy weather. Finally, we include *Season fixed effects* in the regression.

Table 2 reports the summary statistics of as well as correlations between the dependent and the explanatory variables used in the following multivariate analysis. Correlations are relatively low, indicating that collinearity of covariates should not be a concern. As shown in the table, 16% of the teams are made of four key engineers, 62% are made of 3 engineers, and the remaining 22% consist of 2 key engineers. The average value of *Overlap I* is 1.01 and it varies between 0 and 3, while the average value of *Overlap II* is 0.24 and it ranges from 0.02 to 0.65. Prior to joining their current team, the team members have cumulated experience in an average of 6.15 fields, with a minimum of 1 and a maximum of 13 fields. Moreover, on average a team has 41.1 years of cumulative experience in Formula 1, with a minimum of 8 and a maximum of 68 years. As for the team principals, 22% are former engineers, while 46% are former drivers. The team principals have worked for a total of 13 constructors, of which 20% are works teams. Their average yearly budget is 77M real USD. Twenty-one of them won the Constructor World Championship in at least one of the previous 5 seasons. As for the drivers, 13% of them have been awarded, at least once, the Driver's World Championship.

⟨ Insert Table 2 about here ⟩

We first estimate an OLS model in which we regress the performance of a car at the race level on each of our overlap measures and controls. We cluster standard errors at the level of the team. As a robustness check, we also estimate a Tobit model which takes into account the fact that the dependent variable is right-censored. In none of the models, we estimate we control for team fixed effects. The reason is that our regressors of interest, the overlap measures, are defined at the team level and, therefore, their effect on a car's performance would be "swept away" by the within estimator of the coefficients on the time varying covariates (Oaxaca and Geisler, 2003). However, because it is likely that there are omitted variables that are correlated with both the car's performance and the degree of overlap in a team we also estimate an instrumental variable (IV) model, using a 2SLS estimator, in which we augment the initial OLS equation with two additional equations, one for each endogenous variable. Potential omitted factors are, for instance, characteristics of other organizational units of the Formula 1 constructors, characteristics of a constructor's suppliers or characteristics of the ownership or sponsorship structure.

In the IV model, which uses the *Overlap I* measure and its squared term, we instrument the two endogenous variables with the squared term of *Experience breadth*, as well as the share of key engineers for whom English is (one of) their mother tongue(s), the share of key engineers for whom French is their mother tongue, and the share of key engineers for whom Italian is their mother tongue. We justify the adoption of the first instrument on the ground that the squared term of an explanatory variable can be used as instrument as long as it has no direct effect on the dependent variable, i.e. performance (Wooldridge, 2002). An attentive study of the plot of a car's performance on *Experience Breadth* reveals that the relation between the two variables is linear, providing support for the use of the squared term of *Experience Breadth* as an instrument. As for the other instruments, discussions with experts in the field revealed that key engineers who work for British, French, and Italian Formula 1 R&D teams have very distinctive characteristics which leads us to consider them as belonging to a British, a French, or an Italian "School". Our prior is that belonging to one of these Schools might affect the engineers' professional cursus and, hence, their areas of experience, which ultimately impact the overlap measure. We expect these variables to affect the performance of a car either through our overlap measure or through *Experience Breadth*, which we control for in our model. We label the instruments used as *share EN*, *share FR*, and *share IT*. We include the squared terms of these shares to account for non-linearities in the relationship between these shares and *Overlap I*. In the model that uses *Overlap II* and its squared term as explanatory variables for the performance of a car, we use the same instruments as the ones described above but without including the squared terms of the language shares. This choice is grounded on an attentive study of the plot of our endogenous variables on the instruments.

3.3 Results

Table 3 shows the regression results for the performance of a constructor's fastest car as a function of the level of knowledge overlap within a team and other controls. We present the results using first the *Overlap I* measure (*Models 1a, 2a, and 3a*) and then the *Overlap II* measure (*Models 1b, 2b, and 3b*). For each model, we present OLS regression results. As a robustness check, we also present the results of a Tobit regression. The estimated coefficients are marginal effects of the independent variables on the (unobserved) uncensored variable. Our inference and model testing are based on these coefficients. Finally, we also present the results of an instrumental variable (IV) estimation which accounts for potential omitted variable bias.

⟨ Insert Table 3 about here ⟩

We first describe the results of *Models 1a and 2a*. The coefficient of the overlap measure derived from the OLS regression is positive and that of its squared term is negative. A F-test on the coefficients rejects the null hypothesis that these are jointly equal to zero at the 5% confidence level. Given that the coefficient of the overlap measure is 0.64 and that of its squared term is -0.63, this suggests that the optimum is reached for a value if the overlap index that is equal to 1.22. For values of the index greater than 1.22, the performance of a car declines. The results regarding the sign of the coefficients and their joint significance hold when we estimate a Tobit model. The relationship we found between the level of overlap in a team and the performance of a car carries over to the relationship between the value generated from the innovations produced over the life-cycle of the team and its level of knowledge overlap. In fact, having approximated the value produced by a team as the average of the qualifying scores at the race level during the team life cycle, an average of concave functions is concave. This is consistent with our theoretical result that there exists an optimal level of knowledge overlap which maximizes the value generated from the innovations produced by a team.

As expected, if the team principal is a former Formula 1 key engineer, this has a positive impact on the performance of a car. A similar result is found if a team principal is a former driver. These results seem to suggest that the bridge role of a team principal between an R&D top management team and the driver is more effective if the team principal is either a former driver or a former key engineer than if he disposes of a pure managerial background.

As for the other controls, none of the team size dummies are statistically significant. Moreover, a F-test of joint significance of the dummies fails to reject the null hypothesis that they are jointly equal to zero. The relationship between the team's experience in Formula 1 and the performance of a car has an inverted u-shape. The coefficients of *Experience in F1* and *Experience in F1 sqr.* are, respectively, positive and negative. A F-test on these coefficients rejects the null hypothesis that they are jointly equal to zero. As expected, past performance of the team members has a positive and statistically significant impact on the performance of a car. The dummy that takes the value of one if the constructor had kept the same drivers as in the previous season has a positive coefficient in both the OLS and the Tobit regressions, although it is only significant in the OLS regression. Conversely, the dummy that is one if only one of the drivers is unchanged has a positive and statistically significant coefficient in both regression specifications. This provides some evidence that, all else equal, dealing with the same drivers induces economies of learning, and hence cost reductions, which positively affect the performance of a car. A similar result is found for the indicator variable, *Race of the season*, which has a positive and statistically significant impact on the performance of a car. In fact, this result implies that the larger the experience the team has acquired throughout the season, the larger the economies of learning, and the greater the impact on a car's performance. The coefficient of the budget variable and its squared term are positive and statistically significant at the 1% confidence level. This indicates a concave relationship between the financial availability of a constructor and the performance of its fastest car. Finally, past success of a constructor as well as past success of the drivers are positively associated with the performance of a car.

The results of *Models 1b and 2b*, which use the *Overlap II* measure, computed as an Herfindahl Index, confirm the inverted u-shape relationship between the performance of a car and the level of team overlap. The coefficient of this measure and that of its squared term are positive and statistically significant at the 5% confidence level. A F-test on the coefficients rejects the null hypothesis that these are jointly equal to zero at the 5% confidence level. The coefficient of *Overlap II* is 4.19 and that of its squared term is -6.43, suggesting that the optimum is reached for a value of overlap amounting to 0.33. The results regarding the sign of the coefficients and their joint significance hold when we estimate a Tobit model.

As we discussed in the previous section, the results presented so far should be interpreted with caution. In fact, it is likely that there are omitted variables that are correlated with both the car's performance and the degree of overlap in a team. We take this into account and estimate a IV model whose results are presented in the last two columns of Table 3 (*Models 3a and 3b*). A F-test on the joint significance of the instruments in the equations of the endogenous variables suggest that our results should not suffer from a problem of weak instruments. In fact, the results of the F-test in the equations for the overlap measures are well above ten, while those in the equations for the square of the overlap measures are almost equal to ten. The results of the IV regressions confirm that there is an inverted u-shape relationship between the performance of a car and the level of overlap in the R&D top management team, no matter which overlap measure we use. In fact, the use of *Overlap I* and *Overlap II* lead to a positive coefficient of the linear term and to a negative coefficient of the squared term. Both coefficients are statically significant at the 5% confidence level. Moreover, a F-test testing the joint significance of the linear overlap measure and its squared term rejects the null hypothesis that these are jointly equal to zero at the 5% confidence level.

Figure 3 reports the predicted average performance of the constructor's cars during the life time of a top management R&D team, holding all the other controls at their means. These values are computed from the IV models (*Models 3a and 3b*) which use the *Overlap I* measure and the *Overlap II* measure, respectively. Both figures show that there is an optimal level of knowledge overlap, beyond which the value produced by a team over its life cycle declines. This result confirms our prior that beyond a certain level of knowledge overlap the gains in terms of a decrease in coordination costs are offset by the loss in terms of a reduced size of the team knowledge set, and hence a reduced team's ability of solving the problems generated from an innovation project.

⟨ Insert Figure 3 about here ⟩

4 Conclusions

The primary implication of our results is that knowledge overlap matters in R&D intensive teams. The reason is that knowledge overlap is associated with a reduction in a team's coordination costs. This is particularly relevant for R&D teams because innovation activities are characterized by high risk and require large sunk investments, and thus a lack of coordination might result in substantial losses for a firm. It is even more relevant in the case of R&D top management teams given their fundamental role in the design and the organization of an innovation project. However, beyond a certain level of knowledge overlap, the forgone returns from a reduced size of the team knowledge set, which results from the team members having similar knowledge backgrounds, prevail over the reduction in the coordination costs. Therefore, the value from a team's innovations decreases.

We presented a simple model which captures this tradeoff. In this model, a firm manager has to choose the level of knowledge overlap of its R&D team so as to maximize the payoff deriving from the innovations produced by the team during its life horizon. The level of knowledge overlap is determined by hiring team members with a given knowledge background, acquired through past experience. A team lives for n periods and in each period it works on a new innovation project. The value of the resulting innovation is a decreasing function of the level of knowledge overlap within the team. This is because producing an innovation requires the solution of certain problems, and for given knowledge sets of the team members, the smaller their overlap the greater the number of problems whose solution falls within the team's knowledge set. At the same time, the smaller the overlap of the team members' knowledge sets, the larger the initial fixed cost the team members have to incur in order to learn how to coordinate their work. The value of an innovation can only be appropriated by the firm if the innovation meets the requirements of its final users, in which case the firm increments its initial payoff. We solved the model recursively and find that there exists a level of knowledge overlap which maximizes the net present value the firm derived from the innovations produced by the R&D team.

We tested the predictions of the model using a unique dataset of Formula 1 R&D top management teams which operated over the period 1993-2008. These teams are typically made of three key engineers -the technical director, the chief designer, and the chief aerodynamicist- who are in charge of making the most important decisions relative to the performance of a car. The pace at which they take these decisions is high due to rapid technological advancements in Formula 1, to a highly dynamic regulatory environments, and to a high risk of imitation from the part of the competitors.

We built two indexes of knowledge overlap based on the past experience of the R&D top management engineers. The underlying assumption we made was that the team members' knowledge set is determined through their past work experience. Our empirical analysis shows that, having controlled for a large number of factors, there exists an inverted u-shape relationship between the value generated by the top management R&D team at a given period and the degree of knowledge overlap in the team, regardless of the overlap index we use. The optimal level of knowledge overlap is reached for values of the indexes which fall between the 60th and the 70th percentile (*Overlap I*) and between the 70th and the 80th percentile (*Overlap II*). The results on the concave relationship between the value generated by a team at a given period and the level of knowledge overlap is robust to estimating an instrumental variable regression model which corrects for omitted variable bias. In this case, though, the optimal level of knowledge overlap occurs for lower levels of the indexes. Given the way we measure a team's life-cycle value, the inverted u-shape relation we found between the performance of a car at a given race and the level of team knowledge overlap carries over to the relationship between overlap and the value the team generates during its life-cycle. This result confirms our prior that there exists an optimal level of knowledge overlap which resolves the trade-off between the benefits of reducing coordination costs and the costs of decreasing the size of a team's knowledge set. As an additional result, we find some evidence that the value generated is positively related to having a team principal who is either a former Formula 1 driver or a former Formula 1 key engineers. We interpret this result as the team principal having a greater capacity of bridging the R&D top management team and the drivers, provided that he has some experience in either one of the two domains.

These results can be certainly reconciled with earlier findings that task specialization boosts team productivity (Becker and Murphy, 1992; Lazear, 1998; Conti et al., 2011). In fact, the benefits from specialization can only be appropriated by a firm if the members of a team efficiently coordinate their specialized tasks. Efficiency, in turn, is achieved by minimizing the costs of coordination, which can be obtained by hiring team members with a certain level of knowledge overlap.

These findings shed some light on the mechanisms that govern R&D teams. Indeed, the organization of Formula 1 R&D teams is not only relevant for the motorsport industry. Many of the innovations that were initially introduced in Formula 1 have then been applied in the automotive sector, as well as in the sailing and in the aerospace domains[18]. Additionally, the results from this study can be easily extended to teams operating in other R&D intensive sectors. In fact, it is very likely that for these teams the corresponding firm manager faces a similar trade-off as the one we have shown for Formula 1 teams.

Finally, a few caveats are in order. First our overlap measures assume that the team members' knowledge sets are determined by their past work experience. Even though we believe this channel is important, there are certainly other channels through which team members can accrue their

[18]See $http://www.boeing.com/news/releases/2004/q2/nr_040617p.html$ and The Economist's article "Formula 1 goes sailing", September 3rd, 2001.

knowledge. Moreover, our data does not allow us to weighting our indexes by using the number of years the team members have worked in a certain field. Despite this limitation, we believe that given the distinctive characteristics of the areas of experience we consider, the team members' binary experience in these areas is still a reasonable proxy of their knowledge in that area.

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Table 1: **Relative frequency of engineers with different types of experience by team size (N = 2,359)**

No. of engineers with experience: ***industry***	Team size 2	Team size 3	Team size 4
0	12.93	12.36	5.15
1	57.53	52.11	18.7
2	29.54	28.46	48.24
3		7.07	27.91

No. of engineers with experience: ***other formulas***	Team size 2	Team size 3	Team size 4
0	58.3	12.84	9.21
1	29.15	50.41	47.43
2	12.55	24.46	39.02
3		12.3	4.34

No. of engineers with experience: cart	Team size 2	Team size 3	Team size 4
0	100	71.06	66.67
1	0	28.94	33.33

No. of engineers with experience: ***cars for non-commercial events***	Team size 2	Team size 3	Team size 4
0	80.69	41.51	56.91
1	13.13	50.61	23.58
2	6.18	7.88	19.51

No. of engineers with experience: ***other F1 constructors***	Team size 2	Team size 3	Team size 4
0	12.93	4.42	0
1	64.29	21.13	0
2	22.78	37.57	23.85
3		36.89	42.82
4			33.33

Table 2: **Descriptive statistics (N = 2,359)**

		mean	s.d.	min	max	1	3	2	4	5	6	7	8	9	10	11	12	13	14	15
1	Performance	-2.30	1.84	-32.05	0	1														
3	Overlap I	1.01	0.74	0	3	0.14	1													
2	Overlap II	0.24	0.13	0.02	0.65	0.11	0.94	1												
4	Team_size_2	0.22		0	1	-0.16	-0.21	-0.04	1											
5	Team_size_3	0.62		0	1	0.04	0.07	0.06	-0.68	1										
6	Team_size_4	0.16		0	1	0.13	0.14	-0.03	-0.23	-0.55	1									
7	Experience breadth	6.15	2.64	1	13	0.26	0.75	0.68	-0.52	0.16	0.38	1								
8	Team tenure	0.77	1.24	0	6	0.13	-0.01	0.04	0.24	-0.05	-0.20	-0.14	1							
9	Experience in F1	41.10	13.31	8	68	0.29	0.25	0.12	-0.64	0.25	0.40	0.47	-0.02	1						
10	Average age	42.70	3.52	32.33	49	0.18	0.14	0.10	-0.10	-0.10	0.25	0.28	0.12	0.49	1					
11	Share EN	0.60	0.34	0	1	0.13	0.46	0.46	-0.14	0.02	0.14	0.34	0.05	0.29	-0.12	1				
12	Share FR	0.11	0.21	0	1	-0.13	-0.25	-0.24	0.13	-0.03	-0.11	-0.25	0.00	-0.09	-0.06	-0.38	1			
13	Share IT	0.07	0.15	0	0.67	-0.17	-0.26	-0.30	-0.13	0.09	0.03	-0.24	-0.14	0.04	-0.08	-0.43	-0.06	1		
14	Former productivity	0.14	0.21	0	0.67	0.26	0.07	0.04	-0.27	0.33	-0.13	0.20	0.08	0.26	0.27	-0.09	-0.06	-0.07	1	
15	TP former engineer	0.22		0	1	0.10	-0.40	-0.33	0.33	-0.26	-0.03	-0.29	0.14	-0.07	0.06	-0.14	0.03	-0.11	0.08	1
16	TP former driver	0.46		0	1	0.04	0.15	0.16	-0.11	0.18	-0.11	0.14	-0.08	0.09	-0.06	0.25	0.07	-0.19	-0.05	-0.50
17	Same drivers	0.32		0	1	0.22	0.21	0.22	-0.10	0.11	-0.03	0.21	0.10	0.23	0.20	0.02	-0.02	-0.11	0.12	0.04
18	One driver the same	0.49		0	1	-0.05	-0.09	-0.09	0.10	-0.11	0.04	-0.09	-0.01	-0.13	-0.15	0.07	0.04	-0.02	-0.12	0.04
19	All new drivers	0.20		0	1	-0.19	-0.14	-0.15	0.002	0.01	-0.01	-0.13	-0.11	-0.10	-0.05	-0.11	-0.03	0.15	0.02	-0.09
20	Works team	0.20		0	1	0.29	0.22	0.14	-0.18	0.01	0.19	0.22	0.06	0.36	0.49	-0.18	-0.25	0.15	0.31	-0.09
21	Budget [100M US$]	0.77	0.58	0.05	2.15	0.44	0.07	0.03	-0.23	-0.05	0.34	0.25	0.05	0.56	0.48	0.08	-0.32	0.03	0.30	0.21
22	WC constructor	0.21		0	1	0.35	0.05	0.05	-0.16	0.23	-0.12	0.13	0.30	0.28	0.00	0.22	-0.02	-0.07	0.23	0.05
23	WC driver	0.13		0	1	0.27	0.15	0.15	-0.08	0.13	-0.09	0.14	0.090	0.14	0.11	0.10	-0.13	-0.10	0.34	-0.04
24	City track	0.12		0	1	-0.07	0.003	0.003	-0.01	-0.01	0.01	0.01	-0.002	0.01	-0.001	0.002	-0.003	-0.002	-0.004	-0.002
25	Rainy_weather	0.14		0	1	-0.01	0.002	0.02	0.003	0.03	-0.05	0.02	0.01	-0.04	-0.05	-0.01	0.04	-0.02	0.02	-0.02
26	Race of the season	8.94	4.90	1	19	0.08	0.002	-0.01	-0.01	-0.02	0.04	0.005	-0.01	0.03	0.03	0.01	-0.02	0.01	-0.01	0.01

		16	17	18	19	20	21	22	23	24	25	26
16	TP former driver	1										
17	Same drivers	-0.01	1									
18	One driver the same	-0.02	-0.66	1								
19	All new drivers	0.04	-0.34	-0.48	1							
20	Works team	-0.08	0.28	-0.20	-0.08	1						
21	Budget [100M US$]	-0.10	0.31	-0.13	-0.20	0.64	1					
22	WC constructor	0.003	0.17	-0.05	-0.13	0.18	0.28	1				
23	WC driver	0.08	0.17	-0.13	-0.03	0.27	0.24	0.30	1			
24	City track	0.001	0.01	0.00	-0.004	0.002	0.004	0.001	0.03	1		
25	Rainy_weather	-0.01	-0.02	0.04	-0.03	-0.04	-0.06	0.03	-0.01	-0.06	1	
26	Race of the season	-0.01	0.005	0.004	-0.01	0.02	0.04	-0.01	-0.04	-0.29	0.06	1

Pearson correlation coefficients (for two continuous variables) / Point biserial coefficient (for one continuous variable and one dummy variable) / Phi coefficient (for two dummy variables).

Table 3: **Multivariate analysis of performance (N = 2,359)**

VARIABLES	Model (1a) OLS	Model (1b) OLS	Model (2a) TOBIT	Model (2b) TOBIT	Model (3a) 2SLS	Model (3b) 2SLS
Dependent variable				performance		
Overlap I	0.644**	#	0.733**	#	1.216***	#
	[0.262]		[0.286]		[0.427]	
Overlap I (sqr)	-0.263**	#	-0.294**	#	-0.526**	#
	[0.109]		[0.120]		[0.227]	
Overlap II	#	4.190**	#	4.821**	#	13.482**
		[1.758]		[1.940]		[6.295]
Overlap II (sqr)	#	-6.429**	#	-7.272**	#	-29.382**
		[2.801]		[3.059]		[12.509]
Joint F-Test (overlap variables)	3.25 (p=0.044)	3.01 (p=0.054)	3.50 (p=0.0314)	3.291 (p=0.037)	8.40 (p=0.015)	5.53 (p=0.063)
Reference group: Team_size_2 (dummy)						
Team_size_3 (dummy)	0.057	0.186	0.016	0.165	-0.095	-0.890
	[0.279]	[0.320]	[0.300]	[0.353]	[0.371]	[0.919]
Team_size_4 (dummy)	0.282	0.536	0.244	0.539	0.021	-1.070
	[0.387]	[0.460]	[0.431]	[0.530]	[0.543]	[1.237]
Experience breadth	0.055	0.027	0.069	0.036	0.067	0.210
	[0.050]	[0.060]	[0.061]	[0.075]	[0.078]	[0.155]
Team tenure	-0.102	-0.085	-0.138	-0.120	-0.167	-0.130
	[0.131]	[0.132]	[0.139]	[0.139]	[0.144]	[0.188]
Team tenure (sqr)	0.028	0.025	0.040	0.037	0.038	0.026
	[0.024]	[0.024]	[0.027]	[0.027]	[0.026]	[0.034]
Experience in F1	0.031	0.032	0.026	0.027	0.026	0.078
	[0.030]	[0.030]	[0.033]	[0.034]	[0.034]	[0.068]
Experience in F1 (sqr)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
Average age	-0.015	-0.019	-0.023	-0.028	-0.004	-0.033
	[0.025]	[0.024]	[0.028]	[0.028]	[0.025]	[0.038]
Former productivity team	1.081***	1.086***	1.487***	1.500***	1.120***	1.187***
	[0.270]	[0.268]	[0.300]	[0.298]	[0.259]	[0.345]
Reference group: TP employed manager (dummy)						
TP former engineer (dummy)	0.561**	0.584**	0.604**	0.627**	0.486**	0.139
	[0.237]	[0.247]	[0.245]	[0.256]	[0.232]	[0.341]
TP former driver (dummy)	0.334**	0.361**	0.403**	0.434***	0.287*	0.197
	[0.161]	[0.163]	[0.165]	[0.167]	[0.163]	[0.226]
Reference group: All new drivers (dummy)						
Same drivers (dummy)	0.323*	0.336*	0.322	0.338	0.313*	0.450*
	[0.181]	[0.186]	[0.208]	[0.210]	[0.180]	[0.245]
One driver the same (dummy)	0.355*	0.360*	0.369*	0.375*	0.340*	0.372
	[0.187]	[0.191]	[0.208]	[0.210]	[0.186]	[0.235]
Works team (dummy)	-0.030	-0.009	0.056	0.082	-0.090	-0.107
	[0.271]	[0.267]	[0.290]	[0.284]	[0.272]	[0.308]
Constructor's budget [100M US $]	2.949***	2.929***	2.748***	2.718***	2.907***	1.799
	[0.589]	[0.601]	[0.660]	[0.685]	[0.609]	[1.206]
Constructor's budget [100M US $] (sqr)	-0.906***	-0.903***	-0.824***	-0.819***	-0.870***	-0.300
	[0.254]	[0.259]	[0.305]	[0.315]	[0.264]	[0.566]
WC constructor (dummy)	0.683***	0.687***	0.866***	0.872***	0.630***	0.339
	[0.149]	[0.154]	[0.186]	[0.186]	[0.162]	[0.259]
WC driver (dummy)	0.513***	0.490***	0.703***	0.677***	0.518***	0.515***
	[0.126]	[0.125]	[0.176]	[0.175]	[0.124]	[0.144]
Reference group: Purpose built track (dummy)						
City track (dummy)	-0.357**	-0.356**	-0.376**	-0.375**	-0.358**	-0.358**
	[0.148]	[0.148]	[0.154]	[0.154]	[0.145]	[0.145]
Reference group: Dry_weather (dummy)						
Rainy_weather (dummy)	-0.097	-0.096	-0.097	-0.097	-0.099	-0.096
	[0.071]	[0.071]	[0.074]	[0.074]	[0.069]	[0.067]
Race of the season	0.018**	0.018**	0.018**	0.018**	0.018***	0.018***
	[0.007]	[0.007]	[0.008]	[0.008]	[0.007]	[0.007]
Season fixed effects	included	included	included	included	included	included
	F(14,87)	F(14,87)	F(14,87)	F(14,87)	F(14,87)	F(14,87)
Wald-test	=9.92	=8.52	=8.00	=7.03	=129.01	=46.29
p-value	p=0.000	p=0.000	p=0.000	p=0.000	p=0.03	p=0.000
Constant	-5.453***	-5.531***	-5.174***	-5.275***	-5.769***	-5.900***
	[0.941]	[0.944]	[0.983]	[0.994]	[0.951]	[1.406]
Sigma			1.532***	1.534***		
			[0.140]	[0.140]		
Pseudo Likelihood			-4126.59	-4129.14		
Observations	2,359	2,359	2,359	2,359	2,359	2,359
R-squared	0.392	0.391			0.387	0.321
Pseudo R-squared			0.132	0.1316		
F test / Chi2 test	30.23	32.26	31.62	33.29	1110.01	611.86
F test 1sr-stage: overlap	-	-	-	-	28.4 (p=0.000)	14.94 (p=0.000)
F test 1sr-stage: overlap (SQR)	-	-	-	-	8.33 (p=0.000)	7.05 (p=0.000)
Hansen J statistic	-	-	-	-	3.498 (p=0.624)	0.125 (p=0.940)
Instruments	-	-	-	-	cum. no. of fields of experience (sqr), share EN speaking, share EN speaking (sqr), share FR, share FR (sqr), share IT, share IT (sqr)	cum. no. of fields of experience (sqr), share EN speaking, share FR, share IT

OLS, TOBIT, and IV regression analyses, clustered standard errors in brackets (std. err. adjusted for 88 clusters in eng_team_id)
Marginal effects are provided for the TOBIT regression analysis / *** p<0.01, ** p<0.05, * p<0.1 / # not included

Figure 1: **Organizational structure of a Formula 1 constructor**

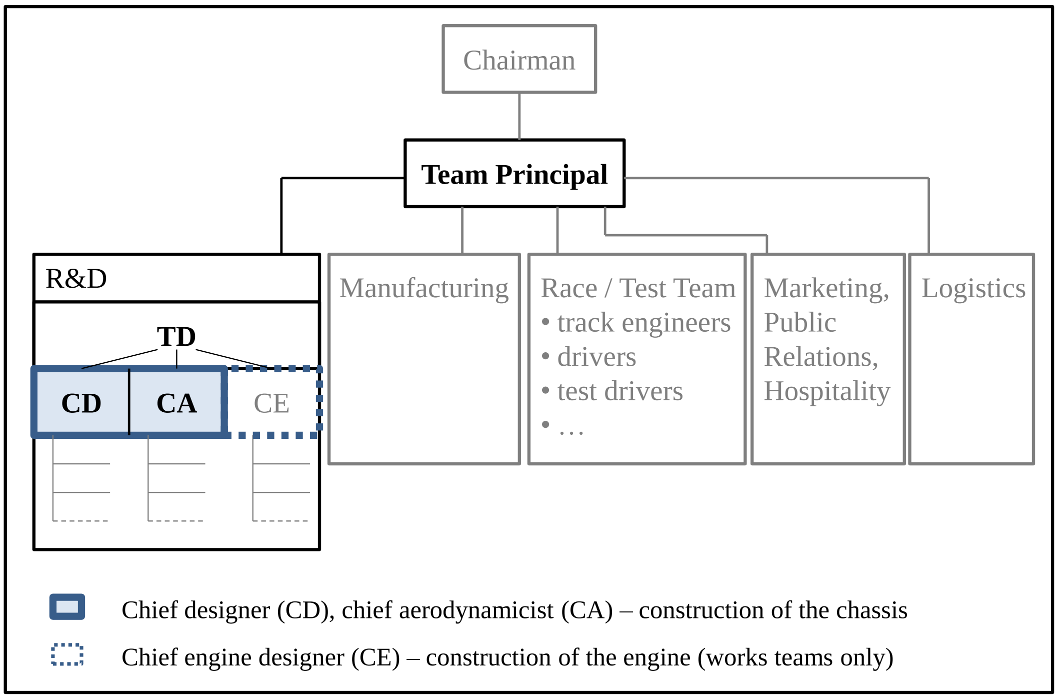

Figure 2: **Distribution of Overlap I and Overlap II (N=2,359)**

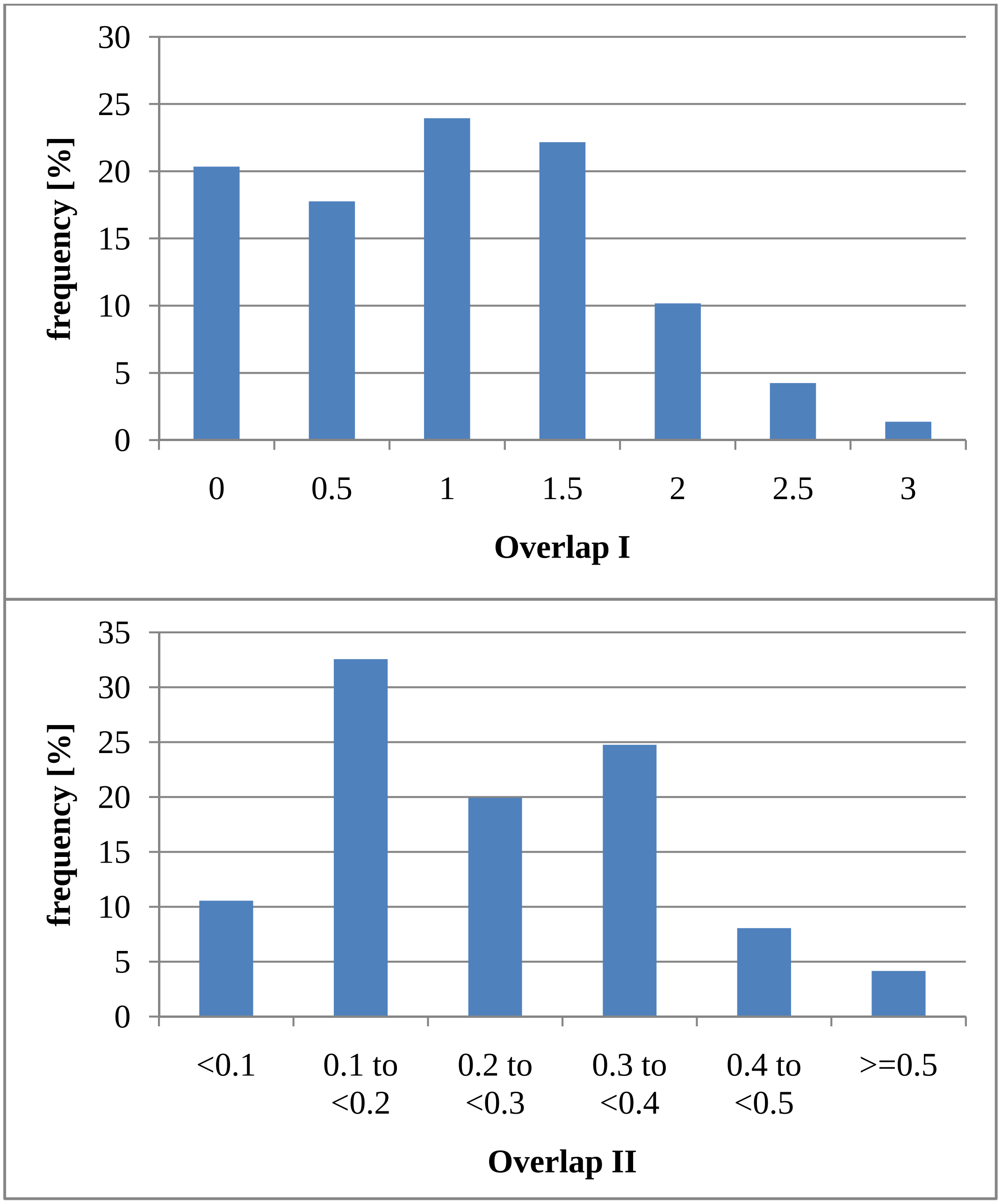

Figure 3: **Effect size Overlap I and Overlap II based on Models 3a and 3b displayed in Table 3 (N = 2,359)**