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Knowledge Diversity & Knowledge Overlap in R&D Teams: Evidence from the Formula 1 Motorsport Industry

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Abstract

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Abstract (150 words)

Analysts of innovation not only diagnose a trend toward collaboration in R&D but also highlight that teams are more likely to generate successful research outcomes. Examining the role of team knowledge in inventive search, existing studies typically conceptualize team knowledge diversity and team knowledge overlap as two ends of a continuum and proclaim an inverse U-shaped relationship between diversity and performance. In contrast, this paper argues, and finds empirical support for the idea that diversity and overlap represent two dimensions of team knowledge. Adopting this novel perspective, our results reveal that the knowledge diversity–performance relationship is positive, and that a certain extent of knowledge overlap can mitigate challenges arising from diversity. Furthermore, this perspective allows us to propose the theoretically appealing and practically relevant concept of “team knowledge configurations”. We test our predictions using longitudinal data covering 88 Formula 1 R&D teams that built 141 race cars during 1993-2008.

Keywords: Innovation; Knowledge Diversity; Knowledge Overlap; Team Configurations.

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1. Introduction

Recent studies on innovation not only diagnose a general trend toward collaboration in R&D (Wuchty, Jones and Uzzi 2007), but also indicate that teams are more likely to generate successful research outcomes, including "inventive breakthroughs" (Singh and Fleming, 2010). Examining the composition of R&D teams, the extant literature typically argues that an inverse U-shaped relationship exists between the diversity of knowledge that a team possesses and its R&D performance: while on the one hand, greater knowledge diversity provides greater recombinant opportunity in the team's inventive search, greater knowledge diversity also means that team members will have to exchange their knowledge with dissimilar others – which is likely to cause problems in communication and the exchange of ideas (Dougherty 1992; Williams and O'Reilly 1998; Leiponen and Helfat 2010). Thus, if a team possesses highly diverse knowledge, it may fail in recombining its knowledge endowments.

In the present study we argue that the proclaimed inverse U-shaped relationship – and the underlying conceptualization of knowledge diversity[1] and knowledge overlap[2] as two ends of one continuum – significantly limits our understanding of collaborative innovation, and may even have produced misleading insights into the team knowledge – R&D performance relationship. Rather, in contrast to the existing literature, we adopt a multidimensional perspective on team knowledge: Specifically, we propose that the knowledge diversity – performance relationship is positive, because the more diverse the knowledge pool of a team, the larger the recombinant potential of the team in its inventive search. Furthermore, we argue that knowledge overlap – which has so far just been treated as the opposite of knowledge diversity – represents a distinct knowledge dimension. Although overlapping knowledge does not add new information to the creative search process, it should facilitate the sharing of knowledge among team members and, in particular, help to mitigate (and potentially overcome) problems that diverse teams often face in knowledge recombination such as idea blocking and miscommunication (Dougherty 1992; Hambrick et al. 1996). In other words, knowledge overlaps between team members may serve as "bridges" that allow their common and their unique knowledge to "travel" and to be recombined in a relatively more efficient and effective manner, thereby leading to superior outcomes in innovation.

Thus, the purpose of our study is to advance understanding of how collaboration in research affects innovation performance by making a conceptual as well as empirical distinction between *team knowledge diversity* and of *team knowledge overlap* and by investigating the unique and the joint effects of these two structural team characteristics on outcomes in innovation. Notably, by disentangling both structural features of team knowledge, one would not only be able to render a more

[1] Following Taylor and Greve (2006), we define team knowledge diversity as the relevant areas in which a team has experience. In particular, we define diversity at the level of the team, i.e., we do not distinguish between teams in which the knowledge endowments are distributed homogenously between different members and those where diverse knowledge endowments are held by one team member.

[2] We define team knowledge overlap as situations in which two or more team members share some knowledge endowment (Cannon-Bowers and Salas 2001). Again, knowledge overlap is defined at the team level.

complete account of the effects of team knowledge in innovation but also begin to study the theoretically appealing and practically relevant concept of "team knowledge configurations". Following this idea, teams can be configured in multiple ways – such as teams with high diversity & high overlap and teams with high diversity & low overlap in their knowledge endowments. In particular, we examine whether (i) teams with the same level knowledge diversity, yet different levels of knowledge overlap, will achieve different performance outcomes in innovation, but also that (ii) certain configurations of team knowledge diversity and overlap may lead to the same (equifinal) performance. If supported, these findings would prove consequential for how we think about the composition of R&D teams, and the antecedents to successful recombinant search processes in innovation.

We inform our theoretical development by drawing on the existing innovation literature (e.g., Singh and Fleming 2010), which highlights the importance of knowledge recombination opportunities in teams, and the cognition and information sharing literatures (Stasser and Titus 1985; Cannon-Bowers, Salas and Converse 1993; Klimoski and Mohammed 1994; Pelled 1996; Mohammed and Dumville 2001), which emphasize that the functioning of teams critically relies on collective sensemaking among team members.

We test our predictions in the context of R&D teams in the Formula 1 motorsport industry. This context is well suited to the focal interest of our research, because Formula 1 is a highly innovative, "fast-paced" industry in which the success of the race car constructors depends on how well and how quickly they can react to changes in the regulatory environments and achieve technological advances. Our unique data set covers the upper echelons of 88 Formula 1 R&D teams that operated and built a total of 141 race cars during the period 1993 to 2008. For these cars, we observe 2,359 qualifying outcomes in Formula 1 World Championship races ("Grand Prix") and can draw on precise and objective performance data over the entire observation period.

The empirical analysis produces two main results in support of our theory: First, we find that team knowledge diversity and team knowledge overlap have distinct effects on R&D performance: While team knowledge diversity has a positive, linear relationship with performance, an inverse U-shaped relationship exists between knowledge overlap and performance, implying that there exists an optimal level of knowledge overlap in teams. Second, our analysis also identifies the performance effects associated with distinct team knowledge configurations. In fact, we find that different team knowledge configurations can lead to equifinal outcomes – which means that agents responsible for configuring R&D teams may trade off some level of knowledge diversity with knowledge overlap. Overall, the results of the present study support our meta-argument for the importance of adopting a multi-dimensional view of team knowledge in our quest to understand collaborative innovation.

2. Knowledge Diversity and Knowledge Overlap in R&D Teams

The knowledge of a R&D team is one of the most critical inputs to the innovation process – from the identification and formulation of problems, to their exploration, interpretation, and solving, and, finally, the dissemination and implementation of the decisions (Hargadon 1998; Dixon 1999). As discussed, this study distinguishes team members' knowledge endowments along two primary dimensions, that is, their knowledge diversity and their knowledge overlap.

Following prior work, we define team *diversity* as situations in which teams dispose of different knowledge attributes (Jackson, Stone and Alvarez 1993; Harrison and Klein 2007). We define team knowledge *overlap* as situations in which two or more team members share some knowledge endowment, and, thus, adopt a definition that is in line with prior cognition research in the realm of teams (cf. Cannon-Bowers and Salas 2001). Hence, whereas diversity reflects the different knowledge bases and perspectives available in organizational problem-solving (Wiersema and Bantel 1992), overlap emphasizes the knowledge and perspectives that are shared between team members. The distinction between knowledge diversity and overlap has also been picked up in recent empirical work, though without examination of the overlap dimension. For instance, Taylor and Greve's (2006) measure of team diversity focused on the experience of creators across different comic book genres and relied on a count of all genres that the creators had worked on in their careers, "omitting double-counts of genres that more than one creator had worked with." (p. 731).

One may be tempted to look at knowledge diversity and knowledge overlap as opposites of each other. Yet, this is not the case, as the example of three R&D teams working in Formula 1 indicates (see Figure 1). Each team consists of three engineers who have Formula 1-relevant experience in one or more of the following areas: industry, CART sport, and Formulas other than Formula 1.[3]

- *Team 1* consists of three engineers who each have experience in one particular area that is relevant to Formula 1, but there is no knowledge overlap between team members. Hence, team knowledge diversity is at its maximum and overlap is zero.
- *Team 2* consists of three engineers who all possess experience in the same area (i.e., racing formulas other than Formula 1). Hence, team knowledge diversity is low (the team only has experience in one out of three possible areas), but overlap is at its maximum.
- *Team 3* consists of three engineers who all possess experience in all three areas. Hence, team knowledge diversity and overlap are at its maximum.

[[Please insert Figure 1 about here]]
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[3] For instance, the engineers may have worked for automotive or aircraft companies. A job in *industry* may enable engineers to gather experience about certain materials or built up a network of suppliers. *CART sport* constitutes a stepping-stone to the higher and more expensive motorsport series. Due to severe budget restrictions, CART sport engineers have to work with relatively cheap (i.e., comparably heavy and inflexible) materials. Hence, they need a good understanding of the fundamental physical principles to be able to design fast cars. *Other formulas* (i.e., lower formulas like Formula 2 or Formula 3) are characterized by high standardization. For instance, engineers working in these formulas learn how to improve race car performance under tight rules governing their work.

These examples indicate that, for instance, a high overlap can be reached both with high diversity (Team 3) or low diversity (Team 2), i.e., the two concepts cannot just be two ends of one continuum but form two different dimensions.

Yet, what complicates an assessment of team knowledge diversity and team knowledge overlap is the fact that both knowledge dimensions are not completely independent from each other, because the level of knowledge diversity encountered in a team sets an important boundary for the level of knowledge overlap that can potentially be observed in that team – i.e., the greater the diversity of the team's knowledge endowments, the more knowledge areas are available in which team members can potentially overlap. Or, stated differently, low knowledge diversity in teams also means that team members can only overlap in the few (in the extreme one) knowledge area(s) that are (is) represented in the team. We will consider this important property in the interpretation of our findings.

In order to develop our theoretical argument, we will study the effects of knowledge diversity and of knowledge overlap. Although the knowledge diversity – performance relationship has been subject of considerable research (e.g., Bantel and Jackson 1989; Taylor and Greve 2006; Finkelstein et al. 2009), we will nonetheless hypothesize about it, since – as mentioned earlier – we do not follow the line of arguments used in existing research (proposing an inverse U-shaped relationship). Furthermore, this relationship lays the theoretical foundation for examining the joint effects of knowledge diversity and knowledge overlap on performance, and thus the idea that R&D teams can be configured in multiple ways once team knowledge is conceptualized with two structural dimensions.

Team Knowledge Diversity & Performance

Innovation critically relies on the recombination of existing ideas and artifacts (Schumpeter 1934; Nelson and Winter, 1982; March 1991; Hargadon 1998). The extant literature suggest that team knowledge diversity will lead to favorable performance outcomes in innovation, because it improves a team's ability not only to identify but also to evaluate solutions (Singh and Fleming 2010):

First, extant work argues that knowledge diversity will facilitate and enhance the problem-solving process, because the team can draw and build on its members' diverse knowledge endowments when searching for a solution (Bantel and Jackson 1989; Taylor and Greeve 2006). On the one hand, the more diverse teams benefit from a greater likelihood that the solution to a given problem is comprised already within the existing knowledge set of the members (Zander and Kogut 1995; Dixon 2000). On the other hand, teams with diverse knowledge also benefit from greater recombinant opportunity in their creative search (Singh and Fleming 2010). In particular, research has shown that knowledge diversity provides rich knowledge stimuli that enable creativity (Bantel and Jackson 1989; Taylor and Greeve 2006). Beyond the broader internal knowledge repertoire, diverse teams also have a greater variety of external networks that can further enrich the team's recombinant search process by way of accessing external knowledge (Ancona and Caldwell 1992; Singh and Fleming 2010).

Second, knowledge diversity is also key to developing perspective on existing knowledge and to understand which of the identified solutions may lead to superior performance outcomes. In particular, existing research argues that the need to reconcile diverse solutions and disconfirming evidence stimulates team discussion, prevents groupthink, helps to surface faulty assumptions and, thus, not only supports the development of original, high quality solutions but also helps in selecting the best opportunities (Bantel and Jackson 1989; Dixon 1999; Singh and Fleming 2010).

These arguments all indicate the benefits associated with knowledge diversity in teams when it comes to creative search and selection processes. Yet, knowledge diversity, if it becomes too large, may also make team functioning and knowledge recombination more difficult (Taylor and Greve 2006; Leiponen and Helfat 2010). Because greater diversity means that team members have to exchange their ideas with dissimilar others, problems in communication and, in particular, in the exchange of ideas may arise (Dougherty 1992; Williams and O'Reilly 1998). In addition, diverse teams may not be able to benefit from the same level of intra-group trust, because they tend to experience lower social integration and are likely to face more pronounced intra-group task conflict than more homogeneous teams (Richard, Murthi and Ismail 2007). As a result, a diverse team may end up with solutions that are not better than the solutions of teams that are less diverse. Overall, the literature suggests an inverse U-shaped relationship between knowledge diversity and performance.

Yet, as discussed, this inverse U-shaped relationship forms the starting point of our critique of existing, one-dimensional conceptualizations of team knowledge. In particular, we argue that increasing diversity does not harm performance as long as the team members still have a common understanding of the different knowledge components available to the team. In other words, the arguments suggesting decreasing performance at higher levels of diversity may rather reflect a lack of overlap than diversity levels that are too high. Yet, once knowledge diversity and knowledge overlap are conceptualized as two different, even though not completely independent dimensions, greater team knowledge diversity per se should not decrease innovation performance. Hence, we hypothesize:

Hypothesis 1: Team knowledge diversity has a positive effect on innovation performance.

Team Knowledge Overlap & Performance

To reiterate, we define team knowledge overlap as a situation in which two or more team members share some knowledge endowment. Although there is no information gained by adding another member who is in the same knowledge category (Shannon 1948), any shared knowledge category (beyond a distinct one) may arguably produce value for the team in that it provides the basis for common understanding of problems, facilitates the sharing of knowledge among team members during problem solving as well as the subsequent implementation of the identified solution. Whereas prior research has examined 2nd order intervening variables such as communication frequency in teams, this has tapped only partially into the potential that a 1st order team structure construct can provide, as scholarly work in adjacent domains suggests. In particular, the notion that overlap in team cognitive characteristics matters has received attention from scholars seeking to understand information sharing in teams (Stasser and Titus 1985), team mental models and shared cognition (Walsh, Henderson and Deighton 1988; Klimoski and Mohammed 1994; Cannon-Bowers and Salas 2001; Mohammed and Dumville 2001). The general thesis of these bodies of work is that shared cognition will improve team efficiency and effectiveness, because team members have an adequate shared understanding of the task, team, equipment, and situation, which in turn helps team processes in a variety of ways; yet, overreliance on shared knowledge may also become a liability (Cannon-Bowers et al. 1993). Studies in this vein have so far not considered that teams may be at the same time diverse and overlap in their knowledge, i.e., that diversity and overlap may be regarded as two key structural dimensions of team composition.

In the following we argue that holding team knowledge diversity constant, the greater the knowledge overlap among team members, the more favorable the performance outcome. Several arguments suggest this type of relationship. First, the act of knowledge recombination and innovation requires knowledge transfers within the team, so that each team member understands the other team members' expertise and is able to integrate the knowledge pieces coherently (Dixon, 2000). The transfer problem is more difficult to the extent that the knowledge involved is complex, noncodified or tacit (Zander and Kogut 1995). Because individuals who have overlap in their knowledge endowments have been exposed to similar social, environmental and organizational events, they possess a shared language, technical understanding, beliefs and values, which are all features that enhance members' ability to exchange knowledge (Dearborn and Simon 1958; Allen and Cohen 1969; Wiersema and Bantel 1992). In other words, team members who have overlapping knowledge benefit from a greater absorptive capacity that facilitates the exchange, coordination and recombination of their knowledge (Cohen and Levinthal 1990; Richard, Murthi and Ismail 2007). In turn, such knowledge overlaps can also support the translation and communication of the external knowledge gathered by a boundary-spanning team member to other members (Dixon 1999).

Second, collective belief structures will affect the speed and flexibility with which problems are solved and implemented. Specifically, shared task-related knowledge helps a team to accomplish the assignment, because individual team members will be able to predict the behavior of other members, coordinate activity with others successfully, and investigate more solutions to a particular problem in a shorter period (Cannon-Bowers et al. 1993; Smith et al. 1994). These advantages should be of particular relevance in high-velocity environments where competitive advantage is often based on the rate at which innovations can be brought to the market (Schoonhoven, Eisenhardt and Lyman 1990; Smith et al. 1994; McGrath 2013).

Third, teams with overlapping knowledge should benefit from greater trust among its members. Trust is of particular importance in innovation, as knowledge recombination activities occur under conditions of risk and uncertainty, where accustomed practices are often questioned, discarded and exchanged for new ones. Yet, such processes bear the risk of team conflict, which could delay decisions. Higher levels of trust, however, allow the team to maneuver through potential conflicts with greater ease (Hambrick et al. 1996; Williams and O'Reilly 1998).

Yet, in spite of these benefits of team knowledge overlap, overreliance on shared information and mental models may also become a liability (Cannon-Bowers et al. 1993). In particular, prior research has shown that because shared information is more likely to enter the discussion than unshared information, teams may not fully benefit from their knowledge endowments (Stasser and Titus 1985; Mohammed and Dumville 2001). For instance, Stasser and colleagues (1989) found that teams were more likely to repeat shared pieces of knowledge rather than unshared pieces after they were first mentioned. Team discussions and judgments thus tend to be dominated by knowledge that members already held in common prior to their meeting, while the unique knowledge of which the other members are unaware, and which has the potential to get the team to identify breakthrough solutions, will not be part of the problem solving process. In addition, teams with significant overlap may not be willing to criticize each other's views, as they see themselves as a group of friends (Souder 1988). Hence, such teams may refuse to abandon consensually validated, but essentially incorrect views of the world ("groupthink").

In sum, we thus propose that team knowledge overlap has a curvilinear effect on performance, such that after a certain level, overlap is likely to underemphasize unique knowledge among the team members and lead to groupthink, which negatively affects performance.

Hypothesis 2: Team knowledge overlap has an inverse U-shaped effect on innovation performance.

If confirmed, our theoretical development leading to Hypotheses 1 and 2 suggests that R&D teams must have access to both dissimilar knowledge and to overlapping knowledge in order to achieve superior innovation performance. As one can deduce from both hypotheses, there should be one particular team configuration that leads to stronger performance outcomes over other configurations: teams characterized by high diversity in knowledge and by medium levels of knowledge overlap. On the one hand, this type of team configuration ensures consideration of problems from a multiplicity of vantage points, the access to varied knowledge endowments, and facilitates the generation of a larger set of alternative solutions (Bantel and Jackson 1989; Gruber et al. 2013). On the other hand, this team configuration also has superior abilities in absorbing and "making sense" of the team's varied knowledge backgrounds given the overlaps in knowledge (Dixon 2000), yet not to the extent where shared mental models become a liability to the team and the potential for individual contributions is lost (Cannon-Bowers et al. 1993). Thus, when combined, Hypotheses 1 and 2 have the following important implication with respect to team knowledge configurations:

Teams configured of members with high knowledge diversity and medium levels of knowledge overlap will outperform other team configurations.

3. Data and Methodology

We tested our hypotheses using a longitudinal data set covering the upper echelons of 88 Formula 1 R&D teams that operated from 1993 to 2008. During this period, the teams built a total of 141 race cars, with an average of 1.8 cars per team. For these cars, we observe 2,359 qualifying outcomes for the respective Formula 1 World Championship races (Grand Prix).

Several features of this empirical context make it well suited for the purposes of the present research. In particular, due to meticulous data gathering in this domain, precise and objective performance data is available for all teams over the entire observation period. Likewise, given the significant public attention to this sport, unusually rich secondary data – for instance, covering team knowledge and important control variables – is available for our estimations. Third, due to the strong competition among constructors and the high-velocity nature of this setting, R&D plays a particularly crucial role in achieving superior performance outcomes. Fourth, all teams pursue the same performance goal: to have a race car that is as quick as possible. The study setting, research design, data and econometric methods are explained below.

A "Fast-Paced" Study Setting: The Formula 1 Motorsport Industry

Formula 1 motorsport is one of the oldest race car series in existence and shares key features with the American IndyCar series. The series is governed by the FIA (the Fédération Internationale de l'Automobile) and is one of the most popular sports around the world, generating 4.4 billion USD of revenues per year. Grand Prix races are held at different locations worldwide on purpose-built race tracks (circuits) as well as on public roads. 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 2004). 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 such as the American IndyCar Series, which allows constructors to buy the chassis of their race cars (FIA 2012).

Within Formula 1, a number of constructors like Ferrari, McLaren, or Williams design, manufacture and race highly specialized single-seater, open wheel race-cars. Constructors are typically medium-sized companies located in Europe, mainly in the region around Oxford in the UK. They operate budgets up to 415 million USD. Each constructor is allowed to compete with two cars.

Formula 1 motorsport is a highly innovative industry at the forefront of technological development in car manufacturing. Both rapid advancement in technology and highly dynamic regulatory environments require continuous innovation by the race car constructors in order to further improve the speed 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. Formula 1 motorsport is also characterized by high labor turnover rates and 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).

The R&D department of a Formula 1 team consists of 15 to 18 engineers and is typically headed by three key engineers: the technical director, the chief designer, and the chief aerodynamicist. In case of works team (i.e., fully integrated constructors that build the chassis and the engines of their cars), the top R&D 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, we control for works teams in our analysis.

We focus our investigation on the upper echelon (Hambrick and Mason 1984) or dominant coalition (Cyert and March 1963) in the R&D team of the Formula 1 constructor. This top R&D team typically comprises the three aforementioned types of engineers (technical director, chief designer, chief aerodynamicist).[4] These key engineers have to work closely together to make sure that the different parts of a car (chassis, aerodynamics, tires, etc.) fit together and have to organize and coordinate the work of other team members so that the team's R&D efforts result in a competitive car.[5]

Each team member is specialized in a different set of tasks: the Technical Director is the head of R&D division and overlooks the design, development and deployment of race cars. Because he is responsible for the performance and reliability of the cars, his main duties consist in ensuring the overall functioning of the cars, and specifically in bringing together chassis, engine, drivers, tires, and other car components. The Chief Designer is responsible for the basic layout of the race car, i.e., for transforming single components with potentially conflicting requirements (chassis, suspension, gearbox, etc.) into a competitive car. He is also responsible for choosing the materials that are used for building a car. The Chief Aerodynamicist heads the aerodynamics division. Aerodynamics has to create downforce in order to keep the car on the track and to increase cornering speed. At the same time, aerodynamics has to minimize air drag that would slow the car down.

These key engineers are headed by the Team Principal, i.e., the CEO of the constructor, who is responsible for management activities such as contracting sponsors and suppliers, recruiting drivers and engineers, and determining wages. Even if the team principal is not responsible for the construction of the car, he has the final say in all strategic decisions.

Sample and Data Collection

In order to test our propositions, we required detailed data on Formula 1 teams, the work experience of the key engineers, the performance of the race cars that they constructed etc. Because this detailed and varied information is not available from a single source, we had to build our dataset by combining several electronic and paper-based sources. Specifically, we extracted data on the composition of R&D teams and on the cars that Formula 1 drivers had driven during our sample period from "www.motorsportarchiv.de". Moreover, we gathered the names of the team principals from Formula 1 yearbooks (Knupp, various years). We obtained data on qualifying classifications from the electronic database "www.motorsport-total.com". We supplemented these data with information retrieved from

[4] For instance, Bruno Mauduit, the former team leader of Renault F1, describes the organization of an R&D team as a pyramidal structure on top of which stands the team's management (Mauduit and Midler 2000).

[5] There are few cases in which a team is made up of only two key engineers. These cases are mainly confined to the early years of Formula 1, when the chief aerodynamicist was not always included in the top R&D team (Autoevolution 2009). 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 when it is assumed that the tasks of a chief designer are more efficiently performed when assigned to two employees. This latter case is more frequent for large constructors.

the biographies of the team principals and the key engineers. We gathered this information through extensive searches of the internet. Finally, we obtained information on the budgets of the Formula 1 constructors from Formula 1 yearbooks, for the years 1993 to 2006, and from Formula 1 financial reports, for the years 2007 and 2008 (Sylt and Reid 2008, 2009).

In total, our final dataset includes 88 Formula 1 R&D teams that operated from 1993 to 2008. During this period, the teams built a total of 141 race cars, with an average of 1.8 cars per team. For these cars, we observe 2,359 qualifying outcomes for the respective Formula 1 World Championship races. The teams were employed by 13 Formula 1 constructors and managed by 32 team principals. The average team tenure is 1.8 years (minimum of 1 year, maximum of 7 years).

Measures

Dependent Variable: Race Car Performance

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 the R&D team during an innovation project by the percentage deviation of their race car's qualifying time from that of the fastest car during the qualifying session occurring on the Saturday before a Sunday race. During this session each driver has a number of trials (flying laps) to determine the grid position of his car during the race. Because there are significant advantages in starting a race at the head of the grid (the pole position), Formula 1 drivers compete vigorously for the starting positions in each Grand Prix race.

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

$$Performance = \frac{q_i - q_{pole}}{q_{pole}} \tag{1}$$

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, before using it in the regression, we multiply the ratio by (-1). Hence, higher values of the dependent variable indicate better performance.

Note that by using the qualifying time of a car during the pre-race knockout session, we obtain a better indication of the innovation value produced by an R&D team than by using the time at the actual race. This is because competing cars are not allowed to block each other during qualifying sessions, whereas race outcomes are affected by accidents and strategic considerations like refueling or changing tires – which could bias our results. This said, however, we also note that qualifying outcomes do not depict a "perfect" performance measure, since, for instance, overtaking does not play a role during qualifying sessions. Overall, we follow Bothner, Kim and Smith's (2012) research in NASCAR and prefer the qualifying performance over the race performance.[6]

Each constructor is allowed to race with two cars per Grand Prix. Because the performance of a race car during the qualifying session can be influenced by driving errors or the driver's physical

[6] As a robustness check we created a second performance measure, i.e., the points the drivers scored per race. The signs of the coefficients are the same even though the significance of the effects is weaker due to the different factors affecting performance, which are not directly related to technical performance (e.g., collisions).

condition – all of which are independent of the technical achievements of the R&D teams – we only consider the qualifying performance of the faster of the two cars.

Independent Variables

Through extensive examination of the team members' curricula as well as related literature we identified five major areas in which the upper echelons of R&D teams have gathered Formula 1-related work experience. These are: *industries other than motorsports, CART sport, Formulas other than Formula 1* (e.g., F2, GP2, F3000), *Formula 1 constructors other than the current one*, and *race car building for non-commercial events*:

Experience gathered in *industries other than motorsports* was found to greatly help an engineer create a network of suppliers or other partners. For instance, prior to joining Formula 1, Rory Byrne (a star engineer at Benetton F1 and Ferrari F1) 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 (Grandprix 1996). Experience in *CART sport* (or go-kart), a stepping stone to the higher and more expensive motorsport series, helps the engineers to understand the fundamental physical principles of the cars, since they have to work with cheap, i.e., heavy and inflexible materials. CART sport also provides a learning environment for engineers and drivers, since it brings an awareness of the various Formula 1-relevant parameters that can be altered to try to improve performance of the car, like tire pressure, gearing, seat position, chassis stiffness. Work experience in *other formulas* helps an engineer to increase the speed or the reliability of a race car or to deal with standardization of the chassis of the cars. While working for *different Formula 1 constructors*, engineers have access to the knowledge accumulated by these constructors. When an engineer moves to another constructor, he takes with him this knowledge and applies it to the construction of new cars. For instance, Niccolo Petrucci, chief aerodynamicist at Toro Rosso, mentioned that in setting the aerodynamic properties of the car "Toro Rosso STR 6" (2011 season), he drew from experience collected at Ferrari F1 in 1992 (F1 Technical 2011). Finally, car construction for *non-commercial events* – typically done by "one-man teams" – helps an engineer to combine different components of a car and to deal with budget constraints. Adrian Newey, one of the star designers in Formula 1, points out that his experience in race car construction for non-commercial events was key to learning how to improve a car's performance (Grandprix 2013). In particular, engineers learn how to bring the different parts of the car together, since – during their leisure time – they typically act as "one-man team".

Based on the five aforementioned areas of job-related work experience, we constructed our focal Team Knowledge Diversity and Team Knowledge Overlap measures in the following ways:

Team Knowledge Diversity. Following prior research (e.g., Taylor and Greve 2006) we use a richness measure, which is defined as the number of fields (between 1 and 5) in which at least one of the team members has gathered prior work experience.

Team Knowledge Overlap. Knowledge overlap occurs if at least two team members share the same knowledge endowment (Taylor and Greve 2006). In order to measure the level of knowledge overlap in a team, we built an index that takes a score of 1 if all three team members had experience in any of the five areas mentioned above, a value of 0.5 if two of the three team members had experience in this area, and a value of zero if only one, or none, of the team members had experience in this area.[7,8] We summed the area-specific scores across the five areas in order to obtain our knowledge overlap index; it varies between 0 and 3, with higher values indicating a larger knowledge overlap within the R&D team.

In extension to the main analysis, we estimate our models replacing our diversity index with two traditional diversity measures – the Herfindahl Index and the Shannon Index:

Herfindahl Index (HI). This index is defined as the sum (across fields of experience) of the square of the share of team members who have experience in field *i*.

Shannon Index. The Shannon index (SI) is calculated as $-\sum_i P_i(\ln P_i)$, for $i = 1$ to I, where I denotes the number fields of experience and P_i is the proportion of engineering team members with job experience in field *i*.

The Herfindahl and Shannon measures confound the notions of knowledge diversity and knowledge overlap in teams and, thus, mask these important structural characteristics of teams. To obtain an intuitive understanding of this confounding effect, Table 1 shows the calculations of index values for different team knowledge configurations. As an illustration, consider Teams 2 and 6: Team 2 consists of three engineers who each have work experience in five different fields. Hence, both diversity and overlap are at their maximum in this team. Team 6 is also characterized by high knowledge diversity (as the team can draw on work experience in each of the five fields), yet its team members do not overlap at all in their knowledge endowments. As can be seen in Table 1, both the Shannon Index and the Herfindahl Index are highly similar for these fairly different teams ($HI_{team\ 2}$ = 0.8; $HI_{team\ 6}$ = 0.78 / SI_{team2} = 1.61; SI_{team65} = 1.56), which indicates that none of these traditional measures can capture the differences in knowledge configurations of these teams, and that each measure confounds team knowledge diversity and knowledge overlap. In contrast, our measures for knowledge diversity and knowledge overlap are able to capture these important distinctions: knowledge diversity is equal to "5" for both teams, whereas overlap has the value of "5" for Team 2 and of "0" for Team 6.

[[Please insert Table 1 about here]]

Control Variables

Given the rich data that is available in Formula 1 racing, we were able to control for a large number of team- and organizational-level characteristics that are likely to influence performance outcomes in innovation.

[7] Note that results remained robust when we employed other thresholds (e.g., 0, 1, and 2).

[8] In case 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.

Team size. Because team size is an important indicator of the human capital available in a team (Wiersema and Bantel 1992) and is likely to be positively correlated with team diversity (Bantel and Jackson 1989), we control for the size of the R&D team using three dummy variables that flag teams of two, three or four members.

Team tenure. Collaboration experience may facilitate communication among team members (Dixon 1999). Following prior research (e.g., Taylor and Greve 2006), we thus control for team tenure, that is, the number of Formula 1 seasons during which a given team remained unchanged.

Team experience in F1. As innovative output critically depends on the accumulation of prior knowledge (Cohen and Levinthal 1990), we control for the R&D team's experience in Formula 1 with a measure that is defined as the sum of the number of years each team member has worked in Formula 1. We also include a squared measure, because most managerial learning tends to occur during the first years of activity in a particular setting (Finkelstein and Hambrick 1996).

Team average age. We also control for the average age of the team members. Yet, we do not examine age heterogeneity within a given team (e.g., Bantel and Jackson 1989; Pelled 1996), as this dimension varies very little across the teams in our sample.

Former productivity team (non-F1). We use the share of team members who have won a championship title in a race series different than Formula 1 to control for team member quality.

Work experience team principal. Because a Team Principal with first-hand experience either as a race engineer or race driver (in Formula 1 or other race series) better understands how an innovation meets the needs of its users (i.e., the drivers), as compared to a principal who has held solely managerial positions in the past, we include three dummies capturing these distinct background characteristics.

Change in drivers. The innovations implemented in a race car have to be tailored to the characteristics of the drivers. Becoming acquainted with these characteristics entails a cost for the engineers, which is lower if the drivers do not change from one season to another. We thus constructed 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.

Constructor type. We include a dummy that takes the value of one if a constructors builds both the cars' chassis and the engines (e.g., Ferrari), and a value of zero in the case of pure chassis constructors (e.g., Williams).

Budget. This variable measures the annual budget (expressed in real terms) that is available to constructors for paying drivers, engineers and support staff, chassis (R&D, material, wind tunnel), tires, fuel, transportation, logistics, and public relations. For the sake of comparison, we use budgets without engine costs.

Past performance constructor. We use a dummy variable to control for the past performance of the constructor. It either takes the value of 1 if the constructor was awarded the title of "Constructor World Champion" in any of the prior 5 years, or zero otherwise.

Past performance driver. To account for the quality of a driver, we generated a dummy that is equal to 1 if the driver has won at least one Driver World Championship, or zero otherwise.

Race track. Track characteristics are likely to be correlated with a car's performance since there are some cars that are better equipped for city tracks (e.g., Monaco) and others for purpose-built race tracks (e.g., Silverstone). Typically, cars with a higher top speed or cars with better aerodynamic properties perform better on purpose-built race tracks. We thus control for the characteristics of a race track by using a dummy that is equal to 1 if the race track is a city track, or to zero in case of a purpose-built race track.

Weather. The performance of a race car is affected by the weather conditions during a race. Because we expect rain to negatively affect the performance of a car, we include a dummy variable that controls for weather conditions (1= rain).

Race of the season. This variable takes the value of 1 if a car is competing in the first race of the season, 2 if it is competing in the second race, 3 for the third, etc. It controls for economies of learning emerging over a season. It also controls for different types of innovations, given that innovations at the beginning of a racing season tend to be more radical than innovations later in the season.

Finally, we also include season fixed effects in the regressions.

Analytic Methods

Our dependent variable is a continuous variable that could theoretically vary between zero and infinity, yet empirically the maximum value is 32.05. We employ an OLS regression model to estimate the impact of team knowledge on performance and allow for correlation within the top R&D teams by using a cluster regression. The cluster estimator adjusts the variance-covariance matrix to account for observations of a same team to be correlated. In our regressions we refrain from including team fixed effects, because our regressors of interest (knowledge diversity and overlap) are defined at the team level and, thus, 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, given the rich set of controls we use, this should not be a major concern. Because our dependent variable is constraint, i.e., it cannot become smaller than zero, we also estimated a tobit model as a robustness check. Our results remained robust.

4. RESULTS

Descriptive Results

Table 2 reports summary statistics and correlations between the dependent and the explanatory variables used in the multivariate analysis. Correlations are relatively low, indicating that collinearity of covariates should not be a concern. As shown in Table 3, 16 percent of the teams are made of four key engineers, 62 percent are made of three key engineers, and the remaining 22 percent consist of two key engineers. On average, a team has cumulated 41.1 years of experience in Formula 1, with a minimum of 8 and a maximum of 68 years. The average yearly budget amounts to 77M USD.

[[Please insert Table 2 about here]]

Figure 2 shows the distribution of the performance variable. The distribution is strongly skewed to the right. The shape of the distribution implies that small changes in the performance make a big difference. To provide an example an increase in the performance by 0.5 percentage points equals an average difference between starting position 3 and 1 (i.e., the pole position). Or to provide an extreme example: In 1997, at the French Grand Prix, Austrian Formula 1 driver Alexander Wurz would have started from pole position rather than starting position 7, had he just performed 0.5 percentage points better in the qualifying session.

The histogram of Figure 3 illustrates the distribution of the team knowledge diversity index. The mean is 3.32 and knowledge diversity varies between 1 and 5. The distribution of knowledge diversity is slightly skewed to the left, which suggests that our sample teams are characterized by rather high levels of knowledge diversity. Figure 4 displays the distribution of the team knowledge overlap index. The mean value of the index is 1.01 and it varies between 0 and 3. The distribution of knowledge overlap is skewed to the right, which indicates that low knowledge overlap prevails in our teams. Furthermore, Table 3a shows the results of a cross-tabulation of team knowledge diversity and team knowledge overlap. This table indicates that the two constructs are clearly distinct. Table 3b displays the relative frequencies of the 9 different "knowledge diversity – knowledge overlap" team configurations that will be used in our regression analysis.

[[Please insert Figures 2, 3 and 4, and Tables 2, 3a and 3b about here]]

Multivariate Results

Tables 4 and 5 show the regression results for the performance of a constructor's fastest car as a function of the level of team knowledge diversity and knowledge overlap and other controls. In Table 4, we first estimate an OLS model in which we regress the performance of a car, at the race level, on our control variables. We then add the knowledge diversity measure (Models 2 and 3), the knowledge overlap measure (Model 4), and finally include both focal measures (Models 5 and 6). In Table 5 we include eight dummy variables capturing different team configurations of knowledge diversity and knowledge overlap, with low diversity/low overlap being the omitted configuration.

[[Please insert Tables 4 and 5 about here]]

Model 2 in Table 4 indicates that team knowledge diversity has a positive, linear effect on performance. Model 3 tests a possible inverted U-shaped relationship between diversity and performance, as proposed by the existing literature. Results do not support this non-linear relationship.

Model 4 in Table 4 contains the knowledge overlap variables (linear and squared term). Results show that there exists an inverted U-shaped relationship between knowledge overlap and performance. An F-Test confirms joint significance of the two overlap variables.

Model 5 in Table 4 then adds both focal measures with linear and squared terms. Again, results confirm an inverted U-shaped relationship between performance and knowledge overlap but no significant inverted U-shaped relationship between knowledge diversity and performance. Whereas in Model 3 an F-Test at least confirmed joint significance of the two diversity variables, once overlap is added (Model 5) not even the two diversity variables together exhibit a significant effect. These results provide a first indication that the inverted U-shaped relationship between diversity and performance suggested by the existing literature confounds diversity and overlap effects, and, thus, masks the true diversity-performance relationship.

Model 6 in Table 4 tests our hypotheses. In line with Hypothesis 1, we find that team knowledge diversity has a positive effect on performance. The magnitude of the coefficient suggests that an increase in knowledge diversity by one unit increases performance by 0.14 percentage points. Even though this effect seems to be small, it is not. In case diversity is set from the minimum (=1) to the maximum (=5), performance increases by 0.56 percentage points. In the last section, we mentioned that an increase by 0.5 percentage points leads on average to an improvement from starting position 3 to pole position (starting position 1) and could – in an extreme case (French Grand Prix in 1997) even lead to an improvement from starting position 7 to pole position.

The results in Model 6 also support Hypothesis 2. The coefficient of the knowledge overlap measure is positive and that of its squared term is negative. An F-test on the coefficients rejects the null hypothesis that these are jointly equal to zero at the 1 percent-level. Because the coefficient of the knowledge overlap measure is 0.704 and that of its squared term is -0.239, the optimum value is reached if the knowledge overlap index is equal to 1.47, i.e., for values of the index greater than 1.47, race car performance declines. The predicted average performance effects for the team knowledge diversity and team knowledge overlap measures are displayed in Figure 5. Results are based on Model 6, with all controls held at their means.

[[Please insert Figure 5 about here]]

Table 1 (above) indicated that traditional diversity measures – the Herfindahl index and the Shannon index – are unable to distinguish between knowledge diversity and knowledge overlap in teams. As an extension to our main analysis, Table 6 provides results using the Herfindahl and Shannon indexes. Specifically, Models 1 and 2 show an inverted U-shaped relationship between each of the two indexes and performance. Models 3 and 5 indicate that once we add our measure for knowledge diversity, its coefficient is insignificant. Likewise, Models 4 and 6 reveal that once we add the knowledge overlap measure, its coefficient as well as the coefficients of the Herfindahl and Shannon indexes are insignificant. These results confirm, as already suggested by Table 2, that the

Herfindahl and the Shannon indexes confound team knowledge diversity and overlap, leaving no explanatory power to the isolated knowledge diversity or knowledge overlap measures.

[[Please insert Table 6 about here]]

In a final step, we examine one of the key implications that can be derived from Hypotheses 1 and 2, that is, once knowledge diversity and knowledge overlap are considered, a superior team knowledge configuration exists: teams with high knowledge diversity and medium knowledge overlap. To investigate this implication, we introduce nine dummy variables that capture different team knowledge configurations. Teams having "low knowledge diversity & low knowledge overlap" form the control group (Model 1, Table 5). An F-test on the coefficients rejects the null hypothesis that these team configurations are jointly equal to zero at the 1 percent confidence level. An overview of the performance results is given in Figure 6, which includes arrows indicating equifinal performance outcomes.

[[Please insert Figure 6 about here]]

Several findings from this analysis are noteworthy. First, these results offer insights into the performance effects associated with different team knowledge configurations. In particular, we see that team knowledge overlap plays a key role in affecting performance for given levels of team knowledge diversity. For instance, teams with medium-level knowledge diversity achieve markedly different performance outcomes depending on their level of knowledge overlap (low, mid, high overlap). In other words, by examining not only team knowledge diversity but also team knowledge overlap, one is able to uncover important, yet hitherto masked, differences in team knowledge endowments.

Second, a configurational perspective on team knowledge opens up the possibility to study equifinality in performance outcomes, i.e., the question whether different team configurations lead to equivalent performance. In this regard, a closer look at Figure 5 is instructive. In this figure, we highlighted those configurations (the three distinct team knowledge configurations (C3, C5, C8)) that are equifinal to the "optimal" team knowledge configuration C6; this configuration has the overall largest coefficient (0.96***) and represents a team with high knowledge diversity and medium knowledge overlap. Hence, although our result for configuration C6 would signal support for the proposed superior team knowledge configuration, the equifinality of three other configurations indicates that C6 is not the sole team configuration that leads to the best performance outcome.

Third, building on the equifinality results, the present study allows us to understand how knowledge diversity and knowledge overlap may be used as substitutes for each other when assembling teams. For instance, the equifinality of team configurations C3 and C6 indicates that equivalent performance outcomes can be achieved if diversity is high and overlap is either high or medium.

Robustness Tests

We note that the assignment of engineers to R&D teams is not happening "at random". Hence, our results might be affected by endogeneity. Several robustness tests and considerations indicate, however, that endogeneity should not be an important concern in the present study.

(I) We performed instrumental variables regression by including instruments for the endogenous knowledge diversity and knowledge overlap variables. Discussions with experts in the field indicated that key engineers who work for British, French, and Italian Formula 1 R&D teams have distinctive characteristics, i.e., they belong to a British, a French, or an Italian "school". Our prior is that belonging to one of these schools might affect the engineers' professional career and, hence, their areas of experience, which ultimately affects the diversity and overlap measures. As instruments we used 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. However, even though our instruments worked both conceptually and statistically, they are still weak and therefore not appropriate to claim a "causal" relationship. Nevertheless, it is important to note that the results were robust. As another robustness check we included lagged dependent variables. However, lagged dependent variables bear the risk of autocorrelation, which would increase any potential bias. Hence, even though the results again remained robust, we refrain from using these results as evidence of a causal relationship.[9]

(II) While we do not claim a causal relationship between our key explanatory variables and performance, two distinctive characteristics of the Formula 1 industry suggest that in this particular setting endogeneity should not be viewed as an important concern:

First, technologies and regulations change continuously in Formula 1 – even between individual races in a given season we observe changes in the technology. In contrast, team tenure amounts, on average, to two years and varies between one and seven years. Hence, even if – at the beginning of a Formula 1 season – a team was deliberately "assembled" to meet certain requirements or to accomplish a certain goal, after few weeks the context may have changed so that the team composition at the beginning of the season is no longer optimal. Following this reasoning, we conducted another robustness check: we dropped the first race of each season from our empirical analysis, i.e., we excluded those races for which the team composition should have met the requirements perfectly. Our results remained robust.

Second, endogeneity actually occurs only in those industry settings where teams can be assembled as "required". However, Formula 1 is characterized by strong labor market restrictions, since the total number of Formula 1 engineers is fairly limited. Even if the team principle was aware

[9] Another approach would be to use a pre-post design like a difference-in-difference estimator. Even though the Formula 1 industry is characterized by frequent regulatory changes that would qualify as exogenous shocks, the fact that all teams are hit by such a shock at the same time does not allow creating a control group.

of a "perfect team" that he wants to assemble, the required engineers are typically unavailable. Take the case of one of the most renowned teams in Formula 1: Ferrari. At the end of 2013, Ferrari wanted to hire Adrian Newey, a star engineer employed with Torro Rosso. Even though Ferrari has one of the largest budgets in Formula 1 and, thus was able to offer an attractive salary, Newey refused to move, and Ferrari had to hire an engineer from Lotus.[10]

5. DISCUSSION AND CONCLUSION

Theoretical Implications

Innovation is frequently conceived as a process of knowledge recombination (Schumpeter 1934). As Nelson and Winter (1982, p. 130) put it: "the creation of any sort of novelty in art, science, or practical life—consists to a substantial extent of a recombination of conceptual and physical materials that were previously in existence." Following this reasoning, studies have emphasized the diversity of knowledge that is recombined to achieve (breakthrough) innovation, and have pointed to team-level knowledge diversity as one of the key antecedents to accomplish such outcomes. However, as we have seen in the present study not only the diversity of knowledge available to the team, but also the overlap of team members' knowledge is crucial for achieving superior innovation outcomes. Hence, future research needs to pay careful attention in how differences in both structural team characteristics lead to performance heterogeneity in R&D.

Our findings clearly indicate the value of considering knowledge overlap as an important team characteristic alongside the team's knowledge diversity. Both knowledge dimensions are first-order, structural characteristics of teams that can be actively shaped by managers when assembling teams. In no small part, the key role that team knowledge overlap plays in affecting innovation performance has been neglected in prior studies because research has pointed to unmeasured social psychological concepts as factors influencing team performance (e.g., Eisenhardt and Schonhooven 1990), or has linked team diversity to second-order process variables such as ingroup/outgroup biases, communication, and conflict (e.g., Lorber and Farrell 1991).

Furthermore, we enrich current theorizing on collaborative innovation by developing the concept of team knowledge configurations. As our results indicate, the configuration lens is able to provide important new insights in the analysis of collaborative innovation. Case in point, the performance effects at different levels of team diversity vary substantially across different levels of team knowledge overlap. By looking just at one dimension, these crucial differences would go unnoticed and one's findings may be misleading.

Along these lines, the notion of equifinal performance outcomes is of theoretical interest to innovation scholars, because it indicates that knowledge diversity and knowledge overlap can, to some extent, be substitutes. Managers responsible for assembling R&D teams thus not only have more flexibility in choosing team members from their human capital pool (e.g., in case of labor market restrictions); but knowing about which configurations lead to equifinal outcomes will also

[10] See http://www.ft.com/cms/s/0/3ca0478c-1edd-11e3-b80b-00144feab7de.html#axzz2oJKnxln5, accessed on 02/12/2014.

allow them to consider which configurational solution is most cost-efficient in achieving the desired outcomes.

Limitations

When interpreting the results of this study, several limitations must be kept in mind. In particular, this study examined the role of knowledge endowments of R&D teams in the Formula 1 motorsport industry. While this empirical setting has several benefits for studying the team knowledge–performance relationship, the question about external validity arises, i.e., to what extent can our findings be generalized to other industry settings? We are confident that our results are transferable to other industries, since, first, the Formula 1-related knowledge we identified should also be relevant in other industries. Second, the composition of R&D teams in Formula 1 equals that in other industries. Third, it seems that the industry conditions encountered in Formula 1 motorsport are similar to other high-velocity industry environments, where competitive advantages are quickly eroded and firms' performance depends on the ability to introduce innovative products in short time intervals (Eisenhardt and Schoonhoven 1990; McGrath and MacMillan 2000). Examples of such industries are the software and the information & communication industry. This said, however, we believe that we can make only limited generalizations about the team structure effects in less quickly evolving environments, where teams are less pressed to make speedy decisions in their R&D.

Furthermore, we note that our focal knowledge measures examine team members' knowledge in terms of past Formula 1-related experience. Even though this channel is important, there are certainly other channels through which team members can accrue their knowledge. Moreover, our data does not allow us to weight our indexes by using the number of years the team members have worked in a certain field. In spite of this limitation, we believe that given the distinctive characteristics of the fields of experience we consider, the team members' binary experience in these fields can serve as a reasonable proxy of their knowledge in that field.

Finally, it should be noted that we only observe the top management of an R&D team. Even though these upper echelons of the organization play an important role in the generation of innovation (Hambrick and Mason 1984; Finkelstein et al. 2009), it would nonetheless be interesting to understand the mechanisms that govern teamwork in the rest of the R&D team.

Conclusion

Teams are a particularly intriguing instance of learning and innovation, because team knowledge is a (creative) recombination of what each team member knows (Dixon 1999). By showing that the value derived from R&D teams systematically depends on how the team is configured not only in terms of its knowledge diversity but also its knowledge overlap, the findings of this paper can provide future studies critical information on the trail to a more comprehensive theory of collaborative innovation.

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TABLES AND FIGURES

TABLE 1
Knowledge Diversity and Knowledge Overlap: Comparison of Alternative Indexes

		FIELDS OF WORK EXPERIENCE					(1) Herfindahl Index	(2) Shannon Index	(3) Knowledge Diversity Index	(4) Knowledge Overlap Index
		Field 1	Field 2	Field 3	Field 4	Field 5	$1 - HI_{JI} = 1 - \sum_{i=1}^{I} (P_i)^2$	$SI_I = -\sum_{i=1}^{I} P_i * \ln(P_i)$	$DI = \# areas$	$OI_I = \sum_{i=1}^{I} Y_i$
TEAM 1	Engineer 1	x					$1 - HI_{I1} = 1 - \left(\frac{3}{3}\right)^2 = 0$	0	1	1
	Engineer 2	x								
	Engineer 3	x								
TEAM 2	Engineer 1	x	x	x	x	x	$1 - HI_{I2} = 1 - \left(\frac{0.2*3}{3}\right)^2 * 5 = 0.8$	1.61	5	5
	Engineer 2	x	x	x	x	x				
	Engineer 3	x	x	x	x	x				
TEAM 3	Engineer 1	x					0.44	0.64	2	0.5
	Engineer 2	x								
	Engineer 3		x							
TEAM 4	Engineer 1	x		x			0.67	1.10	3	1
	Engineer 2	x		x						
	Engineer 3		x							
TEAM 5	Engineer 1	x		x			0.74	0.61	5	1
	Engineer 2	x		x						
	Engineer 3		x		x	x				
TEAM 6	Engineer 1	x		x			0.78	1.56	5	0
	Engineer 2		x		x					
	Engineer 3					x				

I = number fields of experience and
P_i = proportion of engineering team members with job experience in field *I*
Yi = 1 if all engineers have experience in a field; 0.5 if 2 have experience in a field; 0 if 1 or none of the engineers have experience in a field

TABLE 2
Descriptive Statistics

	Variable	mean	s.d.	min	max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	performance	-2.30	1.84	-32.05	0	1													
2	overlap	1.01	0.74	0	3	0.14	1												
3	Herfindahl index	0.24	0.13	0.02	0.65	0.11	0.94	1											
4	Shannon index	0.90	0.46	0.10	2.28	0.13	0.94	1.00	1										
5	knowledge diversity	3.32	1.10	1	5	0.21	0.43	0.45	0.50	1									
6	team_size_2	0.22	0.41	0	1	-0.16	-0.21	-0.04	-0.06	-0.46	1								
7	team_size_3	0.62	0.48	0	1	0.04	0.07	0.06	0.07	0.31	-0.68	1							
8	team_size_4	0.16	0.36	0	1	0.13	0.14	-0.03	-0.02	0.12	-0.23	-0.55	1						
9	team tenure	0.77	1.24	0	6	0.13	-0.01	0.04	0.04	-0.06	0.24	-0.05	-0.20	1					
10	experience in F1 team	41.10	13.31	8	68	0.29	0.25	0.12	0.14	0.43	-0.64	0.25	0.40	-0.02	1				
11	average age	42.70	3.52	32.33	49	0.18	0.14	0.10	0.10	0.14	-0.10	-0.10	0.25	0.12	0.49	1			
12	av. former productivity team	0.14	0.21	0	0.67	0.26	0.07	0.04	0.06	0.22	-0.27	0.33	-0.13	0.08	0.26	0.27	1		
13	TP former engineer	0.22	0.42	0	1	0.10	-0.40	-0.33	-0.32	-0.17	0.33	-0.26	-0.03	0.14	-0.07	0.06	0.08	1	
14	TP former driver	0.46	0.50	0	1	0.04	0.15	0.16	0.17	0.18	-0.11	0.18	-0.11	-0.08	0.09	-0.06	-0.05	-0.50	1
15	same drivers	0.32	0.47	0	1	0.22	0.21	0.22	0.22	0.14	-0.10	0.11	-0.03	0.10	0.23	0.20	0.12	0.04	-0.01
16	one driver the same	0.49	0.50	0	1	-0.05	-0.09	-0.09	-0.09	-0.09	0.10	-0.11	0.04	-0.01	-0.13	-0.15	-0.12	0.04	-0.02
17	all new drivers	0.20	0.40	0	1	-0.19	-0.14	-0.15	-0.14	-0.05	0.00	0.01	-0.01	-0.11	-0.10	-0.05	0.02	-0.09	0.04
18	works team	0.20	0.40	0	1	0.29	0.22	0.14	0.13	-0.06	-0.18	0.01	0.19	0.06	0.36	0.49	0.31	-0.09	-0.08
19	constructor's budget	0.77	0.58	0.05	2.15	0.44	0.07	0.03	0.04	0.14	-0.23	-0.05	0.34	0.05	0.56	0.48	0.30	0.21	-0.10
20	WC constructor	0.21	0.41	0	1	0.35	0.05	0.05	0.06	0.23	-0.16	0.23	-0.12	0.30	0.28	-0.003	0.23	0.05	0.003
21	WC driver	0.13	0.34	0	1	0.27	0.15	0.15	0.16	0.15	-0.08	0.13	-0.09	0.09	0.14	0.11	0.34	-0.04	0.08
22	city track	0.12	0.33	0	1	-0.07	0.003	0.003	0.003	0.003	-0.01	-0.01	0.01	-0.002	0.01	-0.001	-0.004	-0.002	0.001
23	rainy weather	0.14	0.35	0	1	-0.01	0.002	0.02	0.02	0.03	0.003	0.03	-0.05	0.01	-0.04	-0.05	0.02	-0.02	-0.01
24	race of the season	8.94	4.90	1	19	0.08	0.002	-0.01	-0.01	-0.01	-0.01	-0.02	0.04	-0.01	0.03	0.03	-0.01	0.01	-0.01

		15	16	17	18	19	20	21	22	23	24
15	same drivers	1									
16	one driver the same	-0.66	1								
17	all new drivers	-0.34	-0.48	1							
18	works team	0.28	-0.20	-0.08	1						
19	constructor's budget	0.31	-0.13	-0.20	0.64	1					
20	WC constructor	0.17	-0.05	-0.13	0.18	0.28	1				
21	WC driver	0.17	-0.13	-0.03	0.27	0.24	0.30	1			
22	city track	0.01	-0.002	-0.004	0.002	0.004	0.001	0.03	1		
23	rainy weather	-0.02	0.04	-0.03	-0.04	-0.06	0.03	-0.01	-0.06	1	
24	race of the season	0.005	0.004	-0.01	0.02	0.04	-0.01	-0.04	-0.29	0.06	1

N=2359; 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 3A
Cross-tabulation: Team Knowledge Diversity and Team Knowledge Overlap Dummies

		Knowledge Diversity Dummy*	
		0	1
Knowledge Overlap Dummy*	0	964	500
		40.86%	**21.20%**
	1	343	552
		14.54%	**23.40%**

* Knowledge diversity and knowledge overlap dummies split at the mean of the variables

TABLE 3B
Team Configurations

KNOWLEGDE DIVERSITY	KNOWLEDGE OVERLAP	share [%]
low	low	22.76
medium	low	8.94
high	low	6.40
low	medium	28.19
medium	medium	12.21
high	medium	5.72
low	high	4.45
medium	high	6.40
high	high	4.93

Table 4
Multivariate Results

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
VARIABLES	performance	performance	performance	performance	performance	performance
DIVERSITY		0.202***	0.386		0.169	0.141*
		[0.070]	[0.378]		[0.366]	[0.084]
DIVERSITY (sqr)			-0.028		-0.004	
			[0.057]		[0.055]	
F-TEST			**4,38**		**1,05**	
			[p=0.015]		**[p=0.229]**	
OVERLAP				0.812***	0.701***	0.704***
				[0.244]	[0.235]	[0.236]
OVERLAP (sqr)				-0.246**	-0.238**	-0.239**
				[0.107]	[0.105]	[0.103]
F-TEST				**8,66**	**4,94**	**4,85**
				[p=0.000]	**[p=0.009]**	**[p=0.010]**
referenve group: team size_2						
team_size_3 (dummy)	0.302	0.190	0.183	0.209	0.124	0.125
	[0.268]	[0.255]	[0.257]	[0.258]	[0.260]	[0.260]
team_size_4 (dummy)	1.090***	0.857**	0.851**	0.866***	0.719**	0.720**
	[0.325]	[0.336]	[0.336]	[0.327]	[0.345]	[0.345]
team tenure	0.035	0.040	0.036	0.007	0.013	0.013
	[0.044]	[0.041]	[0.043]	[0.046]	[0.046]	[0.046]
experience in F1 team	0.064*	0.059**	0.060**	0.050	0.051*	0.051*
	[0.032]	[0.030]	[0.029]	[0.030]	[0.030]	[0.030]
experience in F1 team (sqr)	-0.001***	-0.001***	-0.001***	-0.001**	-0.001**	-0.001**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
average age	-0.013	-0.019	-0.019	-0.006	-0.010	-0.009
	[0.026]	[0.024]	[0.024]	[0.025]	[0.024]	[0.024]
av. former productivity team (outside F1)	1.185***	1.107***	1.096***	1.205***	1.156***	1.158***
	[0.317]	[0.298]	[0.296]	[0.265]	[0.267]	[0.265]
reference group: TP employed manager (dummy)						
TP former engineer (dummy)	0.602**	0.640***	0.677***	0.704***	0.679***	0.674***
	[0.242]	[0.221]	[0.224]	[0.254]	[0.248]	[0.239]
TP former driver (dummy)	0.514***	0.473***	0.483***	0.487***	0.458***	0.456***
	[0.180]	[0.174]	[0.173]	[0.173]	[0.173]	[0.172]
reference group: all new drivers (dummy)						
same drivers (dummy)	0.601***	0.545***	0.543***	0.471**	0.477**	0.477**
	[0.183]	[0.176]	[0.175]	[0.192]	[0.184]	[0.184]
one driver the same (dummy)	0.518**	0.510***	0.510***	0.454**	0.469**	0.468**
	[0.198]	[0.191]	[0.190]	[0.192]	[0.188]	[0.189]
works team (dummy)	0.015	0.192	0.180	-0.071	0.062	0.063
	[0.305]	[0.310]	[0.303]	[0.309]	[0.296]	[0.296]
constructor's budget [100M US$]	1.095***	1.047***	1.057***	1.171***	1.124***	1.123***
	[0.221]	[0.227]	[0.223]	[0.226]	[0.223]	[0.223]
WC constructor (dummy)	0.825***	0.780***	0.774***	0.785***	0.749***	0.749***
	[0.161]	[0.152]	[0.155]	[0.152]	[0.151]	[0.150]
WC driver (dummy)	0.623***	0.581***	0.588***	0.568***	0.561***	0.560***
	[0.132]	[0.129]	[0.128]	[0.124]	[0.125]	[0.124]
reference group: purpose built track (dummy)						
city track (dummy)	-0.358**	-0.357**	-0.357**	-0.357**	-0.357**	-0.357**
	[0.147]	[0.147]	[0.147]	[0.147]	[0.148]	[0.147]
reference group: dry weather (dummy)						
rainy weather (dummy)	-0.084	-0.089	-0.088	-0.089	-0.091	-0.091
	[0.071]	[0.072]	[0.072]	[0.071]	[0.071]	[0.071]
race of the season	0.018***	0.018***	0.018***	0.018***	0.018**	0.018***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
year fixed effects (dummies)	included	included	included	included	included	included
Constant	-5.530***	-5.660***	-5.939***	-5.798***	-5.947***	-5.906***
	[1.214]	[1.087]	[1.246]	[1.036]	[1.163]	[1.013]
Observations	2,359	2,359	2,359	2,359	2,359	2,359
R-squared	0.366	0.374	0.374	0.378	0.381	0.381
F test	25.22	23.72	22.85	29.82	25.83	26.41

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 5 Multivariate Results

	Model (7)
VARIABLES	performance
overlap (low) * diversity (medium)	0.515**
	[0.217]
overlap (low) * diversity (high)	0.915**
	[0.413]
overlap (medium) * diversity (low)	0.534***
	[0.172]
overlap (high) * diversity (low)	0.825
	[0.545]
overlap (medium) * diversity (medium)	0.633***
	[0.202]
overlap (medium) * diversity (high)	0.957***
	[0.298]
overlap (high) * diversity (medium)	0.849***
	[0.209]
overlap (high) * diversity (high)	0.273
	[0.214]
referenve group: team size_2	
team_size_3 (dummy)	0.385
	[0.253]
team_size_4 (dummy)	1.028***
	[0.300]
team tenure	0.018
	[0.045]
experience in F1 team	0.042
	[0.030]
experience in F1 team (sqr)	-0.001**
	[0.000]
average age	-0.006
	[0.025]
av. former productivity team (outside F1)	0.940***
	[0.301]
reference group: TP employed manager (dummy)	
TP former engineer (dummy)	0.676***
	[0.229]
TP former driver (dummy)	0.550***
	[0.158]
reference group: all new drivers (dummy)	
same drivers (dummy)	0.523***
	[0.174]
one driver the same (dummy)	0.502***
	[0.182]
works team (dummy)	0.086
	[0.291]
constructor's budget [100M US$]	1.265***
	[0.220]
WC constructor (dummy)	0.785***
	[0.168]
WC driver (dummy)	0.516***
	[0.137]
reference group: purpose built track (dummy)	
city track (dummy)	-0.356**
	[0.148]
reference group: dry weather (dummy)	
rainy weather (dummy)	-0.091
	[0.073]
race of the season	0.018***
	[0.007]
year fixed effects (dummies)	included
Constant	-5.791***
	[1.093]
Observations	2,359
R-squared	0.386
F test	36.49

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 6
Multivariate Results (Extensions to the Main Analyses)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
ABLES	performance	performance	performance	performance	performance	performance
RSITY			0.131		0.114	
			[0.093]		[0.095]	
LAP				0.233		0.060
				[0.611]		[0.601]
LAP (sqr)				-0.026		-0.003
				[0.231]		[0.244]
dahl Index	5.615***		4.859***	4.336		
	[1.656]		[1.617]	[3.880]		
dahl Index (sqr)	-7.737**		-7.390**	-7.083		
	[2.959]		[2.870]	[6.299]		
on Index		1.723***			1.509***	1.633
		[0.505]			[0.495]	[1.187]
on Index (sqr)		-0.651***			-0.619**	-0.646
		[0.244]			[0.237]	[0.555]
ive group: team size_2						
size_3 (dummy)	0.271	0.271	0.163	0.221	0.179	0.257
	[0.266]	[0.262]	[0.274]	[0.273]	[0.270]	[0.271]
size_4 (dummy)	1.011***	1.001***	0.821**	0.909**	0.841**	0.973**
	[0.340]	[0.335]	[0.372]	[0.384]	[0.363]	[0.376]
enure	0.011	0.010	0.016	0.009	0.015	0.010
	[0.047]	[0.046]	[0.046]	[0.046]	[0.046]	[0.045]
ence in F1 team	0.053*	0.052*	0.055*	0.053*	0.054*	0.052*
	[0.030]	[0.029]	[0.030]	[0.030]	[0.029]	[0.030]
ence in F1 team (sqr)	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
e age	-0.014	-0.014	-0.016	-0.013	-0.016	-0.014
	[0.024]	[0.024]	[0.023]	[0.027]	[0.023]	[0.027]
mer productivity team (outside F1)	1.227***	1.220***	1.173***	1.210***	1.176***	1.217***
	[0.260]	[0.258]	[0.260]	[0.265]	[0.258]	[0.260]
ce group: TP employed manager (dummy)						
mer engineer (dummy)	0.677***	0.673***	0.642**	0.685***	0.641**	0.675***
	[0.257]	[0.254]	[0.246]	[0.253]	[0.246]	[0.250]
mer driver (dummy)	0.482***	0.480***	0.455**	0.484***	0.458***	0.481***
	[0.174]	[0.172]	[0.174]	[0.173]	[0.173]	[0.172]
ce group: all new drivers (dummy)						
rivers (dummy)	0.478**	0.473**	0.492**	0.473**	0.486**	0.471**
	[0.192]	[0.190]	[0.188]	[0.194]	[0.188]	[0.192]
iver the same (dummy)	0.458**	0.458**	0.472**	0.451**	0.470**	0.456**
	[0.191]	[0.190]	[0.190]	[0.193]	[0.190]	[0.192]
team (dummy)	-0.021	-0.006	0.089	-0.051	0.086	-0.017
	[0.306]	[0.305]	[0.286]	[0.317]	[0.285]	[0.313]
uctor's budget [100M US$]	1.123***	1.123***	1.094***	1.156***	1.100***	1.134***
	[0.230]	[0.231]	[0.224]	[0.246]	[0.226]	[0.241]
onstructor (dummy)	0.762***	0.756***	0.726***	0.756***	0.727***	0.755***
	[0.157]	[0.156]	[0.158]	[0.158]	[0.157]	[0.157]
iver (dummy)	0.548***	0.546***	0.544***	0.546***	0.544***	0.545***
	[0.121]	[0.121]	[0.123]	[0.121]	[0.122]	[0.121]
ce group: purpose built track (dummy)						
ack (dummy)	-0.357**	-0.357**	-0.357**	-0.357**	-0.357**	-0.357**
	[0.147]	[0.147]	[0.147]	[0.148]	[0.147]	[0.148]
ce group: dry weather (dummy)						
weather (dummy)	-0.089	-0.089	-0.090	-0.089	-0.090	-0.089
	[0.071]	[0.071]	[0.071]	[0.071]	[0.071]	[0.071]
f the season	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
xed effects (dummies)	included	included	included	included	included	included
ant	-5.918***	-5.985***	-5.974***	-5.853***	-6.027***	-5.965***
	[1.020]	[1.001]	[1.004]	[1.037]	[0.993]	[1.017]
vations	2,359	2,359	2,359	2,359	2,359	2,359
ared	0.379	0.380	0.381	0.379	0.381	0.380
	23.60	24.59	23.69	23.73	24.12	23.83

t standard errors in brackets / *** p<0.01, ** p<0.05, * p<0.1

FIGURE 1
Example of knowledge diversity and knowledge overlap in Formula 1 R&D teams

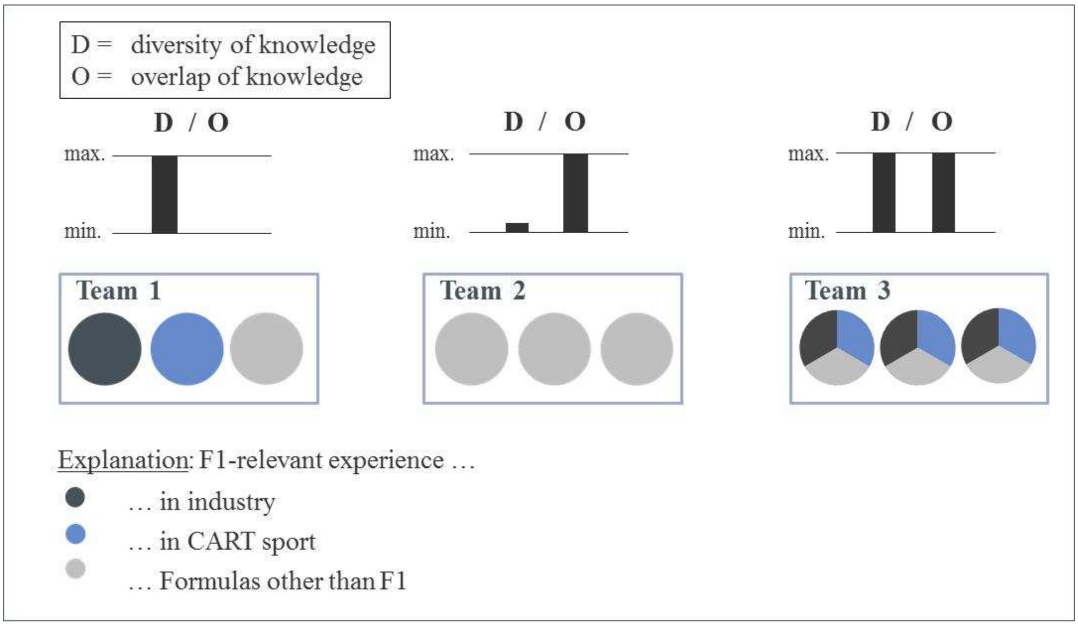

FIGURE 2
Distribution of Performance (N = 2,359)

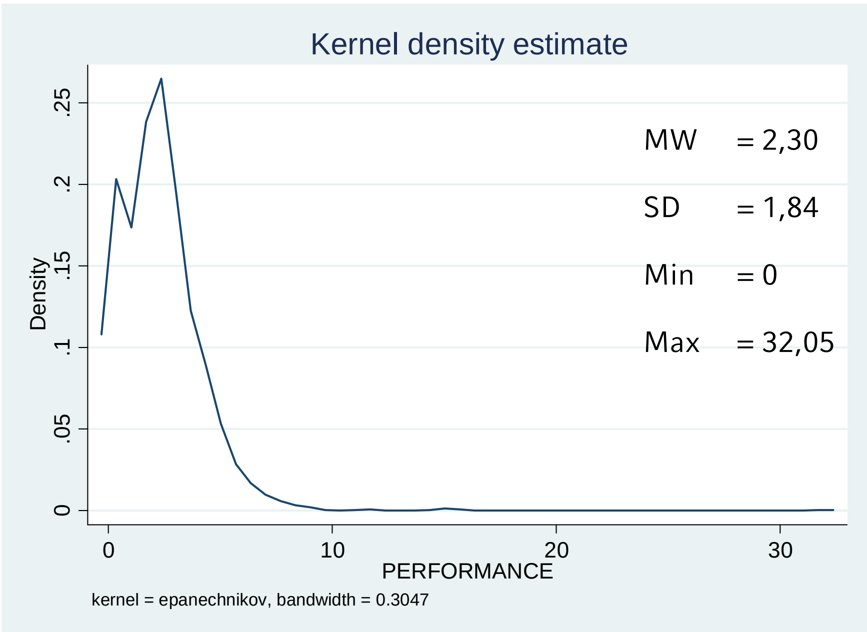

FIGURE 3
Distribution of Knowledge Diversity (N = 2,359)

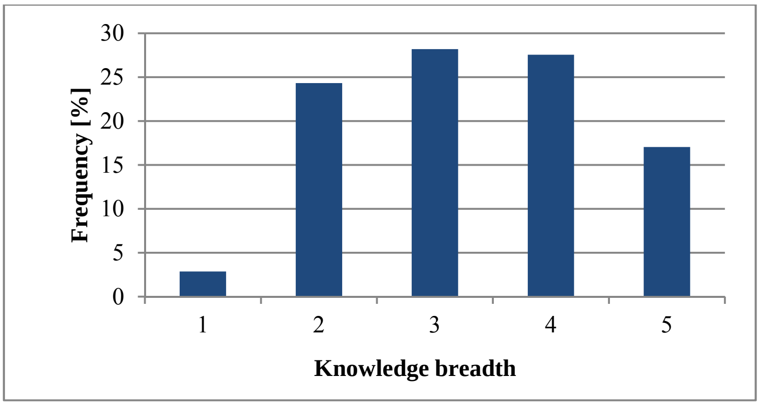

FIGURE 4
Distribution of Knowledge Overlap (N = 2,359)

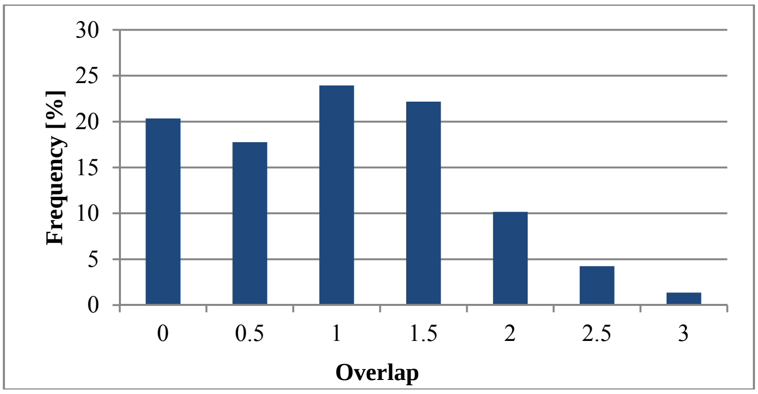

FIGURE 5
Effect Sizes: Knowledge Diversity and Knowledge Overlap (N = 2,359)
(Results based on Model 4 in Table 5)

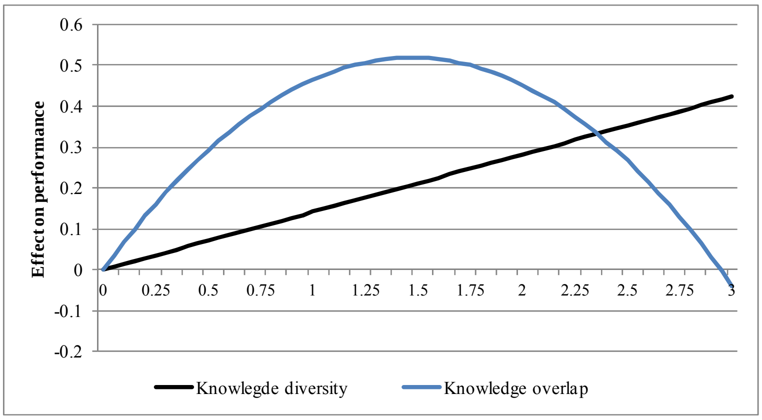

FIGURE 6
Team Configurations: Knowledge Diversity and Knowledge Overlap
(N = 2,359) (Results based on Model 7 in Table 6)

		KNOWLEDGE OVERLAP		
		low	**medium**	**high**
KNOWLEDGE DIVERSITY	**low**	(C1) 0	(C4) 0.53***	(C7) 0.83 *(n.s.)*
	medium	(C2) 0.52**	(C5) 0.63***	(C8) 0.85***
	high	(C3) 0.92**	(C6) 0.96***	(C9) 0.27*(n.s.)*

*** p<0.01; ** p<0.05; * p<0.1 - coefficients not significantly different from the reference group

Equifinal configurations with (C6)

Configuration not equifinal with (C6)