R&D Team Diversity and Performance in Hypercompetitive Environments

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Abstract:

This paper examines the effects of an R&D team's composition on its performance outcomes in hypercompetition. The fundamental feature of firms in hypercompetitive settings is that they are constantly challenged to improve their competitiveness in a relentless race to outperform one another and it is not clear whether firm R&D teams in these settings follow the same paradigms as teams in more stable environments. Analyzing a unique data set from the Formula 1 motorsport racing industry, we find an inverse U-shaped relationship between a team's diversity in task-related experience and its performance – an important result that diverges from well-established theories developed in more stable environments. Fundamentally, we also show that the role of R&D team diversity in experience varies depending on the size of the organizations in which R&D teams operate. While we find a moderating effect for firm age, this effect is not as robust as the effect of firm size. Overall, our findings provide several novel implications for the strategy, innovation, and team literatures.

Keywords: Innovation; Hypercompetition; R&D; Teams; Experience Diversity

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INTRODUCTION

Over the course of the past two decades, strategy scholars have directed their attention to the hypercompetitive nature of many business environments (D'Aveni, 1994; Hambrick, Cho and Chen, 1996; Wiggins and Ruefli, 2005; Sirmon, Hitt, Arregle and Campbell, 2010; McGrath, 2013), emphasizing that it has become increasingly difficult for firms to remain competitive due to intense rivalry, rapid technological change, and high rates of knowledge obsolescence (Eisenhardt, 1989; Bettis and Hitt, 1995; Davis, Eisenhardt and Bingham, 2009; D'Aveni, Dagnino and Smith, 2010). Under such uncertain and volatile conditions, firms are in an "incessant race to get or keep ahead of one another" (Kirzner, 1973: 20).

As can easily be imagined, hypercompetitive environments place critical demands on R&D teams, given that they operate at the locus of firms' inventive activity and are thus one of the most important inputs to the innovation process (Cardinal, 2001; McGrath, 2013). These teams not only have to keep up with the rapid pace of technological change, but they are also challenged to overtake competitors' inventive efforts to bolster their performance (Eisenhardt, 1989; Legnick-Hall and Wolff, 1999). Yet, not just any type of R&D team can achieve the desired performance outcomes in these extreme conditions. Indeed, research on teams operating in highly demanding, uncertain conditions (e.g., fire fighters, SWAT teams, cf. Weick, 1993; Klein, Ziegert, Knight and Xiao, 2006; Weick and Sutcliffe, 2007; Bechky and Okhuysen, 2011) has suggested that it is not only the set-up of a team (in particular, the cognitive resources that a team has at its disposal) that is critical to team performance, but also the preexisting material, cognitive, and social resources that the team can access in its organization (cf. Baker and Nelson, 2005; Miner, Bassof and Moorman, 2001).

Regrettably, we know less than we should about R&D teams operating in hypercompetition – either in terms of how they should be optimally configured to accomplish their challenging work, or in terms of the organizational context that is most conducive to a successful performance. However, given that an increasing number of firms are confronted with hypercompetition, it becomes essential to go beyond merely assuming, or speculating, that existing insights derived from research in more stable environments can be transposed to such extreme settings.[1] In fact, we have reason to believe that they are not: while a meta-analysis of 35 published team studies indicates a *positive* relationship between the task-related experience diversity of teams and their performance (Horwitz and Horwitz, 2007), it has to be acknowledged that greater levels of diversity imply increasing communication and coordination costs and, thus, could lead to a slowdown of the R&D process – which is particularly problematic in the fast-paced environment of hypercompetition. These costs may at some point become so large that they could outweigh any gains from increased diversity, and team performance may actually start to decrease – which suggests an *inverse U-shaped* relationship instead of a positive relationship. Moreover, the existing literature on the team composition–performance relationship tends to be agnostic to the organizational contexts in which teams are embedded (Joshi and Roh, 2009). Yet, as the handful of qualitative studies investigating teams in extreme settings indicate, the organizational context is a fundamental factor that shapes team performance outcomes in hypercompetition.

Given these observations, the present study is not only interested in better understanding how teams should optimally be configured (in terms of their task-related diversity in experience) to achieve superior performance outcomes in hypercompetition, but also how the organizational context (in particular, the size and age of an organization) affects the team diversity in experience–performance relationship in this extreme setting.

We test our set of hypotheses using data from the Formula 1 (F1) motorsport industry. F1 data have recently been used in management research to examine market relationships (Castellucci and Ertug, 2010), knowledge spillovers (Solitander and Solitander, 2010),

[1] This notion echoes more general arguments put forward by strategy scholars pointing out that theories that build on ideas of relative stability rather than rapid change and on the achievement of sustainable rather than temporary advantage (D'Aveni, 1994; Lee, Venkatraman, Tanriverdi and Iyer, 2010) could be of limited value to our understanding of the factors driving performance in hypercompetition – or, even worse, may provide misleading insights (D'Aveni *et al.*, 2010; McGrath, 2013).

technology evolution (Jenkins and Floyd, 2001), competitive balance (Mastromarco and Runkel, 2009), as well as agglomeration and cluster effects (Pinch and Henry, 1999). The F1 context is particularly well-suited to the focal interest of our research because it is a highly competitive, fast-paced industry, characterized by the fact that race car R&D teams' performance depends on their ability to continuously innovate and improve their cars' speed. In the truest sense, these constructors are in an "incessant race to get or keep ahead of the competition", as Kirzner's (1973: 20) quote from our introductory paragraph suggests.

Our unique data set covers the upper echelons of eighty-eight F1 R&D divisions (henceforth referred to as "R&D teams") that built a total of 141 race cars during the period 1993 to 2008. For these cars, we observe 2,359 qualifying outcomes in F1 World Championship Grand Prix races and can draw on precise and objective R&D team performance data over the entire sample period. The fine-grained nature of our data is essential to research seeking to understand the drivers of R&D team performance in hypercompetition, as important relationships could be masked when only course-grained data is available (D'Aveni *et al.*, 2010). We observe performance in the rhythm of Grand Prix races, i.e., every other week during the racing season.

BACKGROUND

Hypercompetition and the limited sustainability of competitive advantage

As previous authors have stressed, hypercompetition is the result of strategic maneuvering among competing firms (D'Aveni, Canger, and Doyle, 1995; Markides, 1999). In his seminal contribution, D'Aveni (1994: 217-218) has defined hypercompetition as "an environment characterized by intense and rapid competitive moves, in which competitors must move quickly to build advantage and erode the advantage of their rivals." Along these lines, scholars such as Bettis and Hitt (1995) and McGrath (2013) have stressed that hypercompetition is characterized by a sustained pace of technological development and the shortening of product life cycles. Others have provided evidence suggesting that it has become more difficult for managers to sustain their firms' competitive advantages over time due to intense competition (Thomas and D'Aveni, 2009).

The notion of hypercompetition builds on ideas originating from the Austrian economics school of thought and, in particular, Schumpeterian theory (Schumpeter, 1939; Kirzner, 1973). Schumpeter (1939: 105) argued that firm profit is "the premium put upon successful innovation in capitalist society and is temporary by nature: it will vanish in the subsequent process of competition and adaptation." Thus, as a result of rapid creative destruction, firms are challenged to constantly develop innovative solutions that allow them to renew their competitiveness over time (Wiggins and Ruefli, 2005; D'Aveni *et al.*, 2010; McGrath, 2013). While scholars have assumed the existence of sustainable competitive advantage since the 1970s and expended considerable effort to investigate its antecedents and implications for firm performance, we are just beginning to understand what it means for firms to establish ever new, short-lived advantages in hypercompetitive settings (e.g., Chen and MacMillan, 1992; Lengnick-Hall and Wolff, 1999; D'Aveni *et al.*, 2010).

R&D teams in hypercompetition

The nature of hypercompetitive environments places challenging demands on the firms' innovation process and, in particular, on their R&D teams, as they govern and shape this process – from the identification and formulation of problems, to their exploration, interpretation, and solving, and, finally, the dissemination and implementation of solutions (Eisenhardt and Tabrizi, 1995; Dixon, 1999; Eisenhardt and Martin, 2000). It is key to recognize that R&D teams operating in hypercompetitive settings must accomplish their work under extreme conditions: they face enormous time pressure, are constantly challenged to perform at the highest level, and have to deal with uncertain information and volatile conditions (Eisenhardt, 1989; Bettis and Hitt, 1995; Davis *et al.*, 2009). For instance, in their day-to-day work they must to anticipate the moves of competing firms, deal with high rates of knowledge obsolescence, and quickly absorb new technological knowledge, as well as generate their own innovations at a rapid pace (MacMillan, 1989).

Although scholars have emphasized the manifold challenges associated with accomplishing rapid innovation in hypercompetition (e.g., D'Aveni *et al*., 2010; McGrath, 2013), we know surprisingly little about the characteristics that R&D teams operating under such extreme conditions must have to achieve superior performance outcomes.

Yet, to obtain initial insights as well as guidance for our study, it is useful to turn to research that has studied teams facing highly challenging conditions in their work – similar to those encountered by teams operating in hypercompetition. We are referring specifically to teams of fire fighters, SWAT teams, extreme action medical teams, or film production crews (e.g., Weick, 1993; Klein, Ziegert, Knight and Xiao, 2006; Weick and Sutcliffe, 2001; Bechky and Okhuysen, 2011). Existing research has shown that teams working in these contexts face severe time pressure, must accomplish their work in uncertain settings and dispose of incomplete information (Klein, Ziegert, Knight and Xiao, 2004).

Importantly, this body of work suggests that to understand team performance in extreme settings both team as well as organizational characteristics must be considered (Moorman and Miner, 1998a; Klein *et al*., 2006; Bechky and Okhuysen, 2011). This research points out that team members do not only have to possess strong task-related experience but must also function in an almost seamless way as a team so that they can react quickly and flexibly to unforeseen occurrences or events (Weick, 1993; Klein *et al*., 2006). In particular, in their in-depth study of the work of SWAT teams and film crews, Bechky and Okhuysen (2011) find that to respond to rapidly changing, surprising conditions, these teams rely heavily on interpersonal collaboration and have a strong common understanding of the tasks to be completed (cf. Klimoski and Mohammed, 1994; Cannon-Bowers and Salas, 2001), that is, an understanding that builds on joint workflow expectations and allows the team to take action in a coordinated manner. Furthermore, the way in which these teams respond to changing conditions showed several characteristics of bricolage and improvisational action (i.e., forms of real-time organizational learning): team members shifted roles, created novel interpretations of their work, and reorganized their routines to reach the level of flexibility required by their dynamic task environment (cf. Eisenhardt and Brown, 1998; Weick, 1993; Miner *et al*., 2001; Baker and Nelson, 2005).

It is important to recognize that the flexibility-enhancing cognitions, actions, and processes of teams operating in extreme settings are supported in key ways by the presence of preexisting organizational resources. Specifically, over time, organizations build up troves of material, social, and cognitive resources that facilitate bricolage and improvisational actions as they allow teams to quickly utilize them in novel ways when responding to dynamic changes in the task environment (Bigley and Roberts, 2001; Miner *et al*., 2001; Bechky and Okhuysen, 2011). For instance, Moorman and Miner (1998b) argued that the declarative and procedural memory of organizations affect the novelty and speed of improvisational action.

Overall, this small and growing body of literature on teams operating in extreme settings sheds important light on how team-level as well as organizational-level features, and their interplay, affect performance outcomes. At the team level, it is both the expertise possessed by individual members and their ability to thoroughly understand the work of other team members that generate the type of strong flexibility that is required to prepare for, proactively shape, and reactively respond to rapidly evolving task environments. At the organizational level, it is the stock of material, social, and cognitive resources that critically supports teamwork, as it enlarges and enriches the teams' potential for action and flexible response.

These insights have important implications for the conceptual framework guiding our own study. Specifically, in order to understand how R&D teams operate under the extreme conditions posed by hypercompetition, our research needs to capture both the characteristics of R&D teams and key organizational features, as the latter shape the material, cognitive, and social resources on which these teams will be able to draw when they engage in their work.

HYPOTHESES

In the following, we develop three hypotheses investigating how the composition of R&D teams affects their performance under the extreme conditions of hypercompetitive environments. Specifically, in our baseline analysis, we study how the diversity of R&D teams' experience endowments affects performance outcomes under such conditions (Hypothesis 1). Building on this baseline relationship, we enrich our theorizing by taking into account that the organizational setting in which these teams operate will differ in terms of the material, cognitive, and social resources available to teams when they are seeking to accomplish their demanding work. In particular, we examine how the size of the firm (Hypothesis 2) and the age of the firm (Hypothesis 3) shape team performance outcomes under extreme conditions. While these core organizational features have been of primary interest to scholars (e.g., Schmookler, 1972; Stinchcombe, 1965; Zenger and Lazzarini, 2004), they have not been studied in relation to team composition (Joshi and Roh, 2009).

R&D team diversity in experience and performance

Building on prior work, we define team diversity as an arrangement in which a team disposes of different types of endowments (Jackson, Stone and Alvarez, 1992; Harrison and Klein, 2007) – in our case, different types of task-related experience. Team members' task-related experience is a key dimension of diversity (Joshi and Roh, 2009) and has particular significance in innovation because exploratory activities are non-routine and thus rely more strongly on flexible inputs than would other types of work activities (Argote, 1999; Dixon, 1999).[2]

In particular, prior research points out that diversity in experience (henceforth, experience diversity) generates fundamental benefits in innovative activities. This is so because

[2] A large body of prior research views team members' demographic backgrounds as determinants of their cognitive bases, that is, their assumptions about the future, cognitive and attitudinal perspectives, perception, knowledge of alternatives, and the consequences attached to alternatives (Dougherty, 1992; Hambrick and Mason, 1984). From an empirical standpoint, a person's demographic background is frequently used as a proxy for cognitive factors that are typically hard to observe, especially when larger scale empirical evidence is sought.

diverse teams are able to draw on a wider set of knowledge, skills, perspectives, and network relationships, and thus cognitive and social resources that critically support the identification and evaluation of solutions. For instance, diverse teams are not only more likely to find the solution to a given problem within their existing experience set and more diverse networks (Dixon, 1999), but also benefit from greater recombinant opportunity in their creative search (Laamanen and Wallin, 2009) – an element that is of major importance in R&D activities, because innovation critically relies on the recombination of existing ideas and artifacts (Schumpeter, 1934; Nelson and Winter, 1982). Team experience diversity is also key to the evaluation of solutions because it allows teams to develop different perspectives on existing insights and pinpoint those solutions that ensure superior performance (Dixon, 1999). In particular, diverse teams are less likely to suffer from groupthink, and ultimately reject faulty presumptions.

As the research on teams operating in extreme conditions suggests, the benefits associated with team experience diversity are likely to matter even more in hypercompetitive settings. This is because such environments demand greater levels of flexibility in the team's response repertoire, novel interpretations of existing and newly acquired knowledge, and varied viewpoints to determine which solution is likely to generate the strongest performance (e.g., Bechky and Okhuysen, 2011). Hence, the aforementioned benefits will increase linearly with team's experience diversity.

Even though there are important benefits associated with team experience diversityit is also important to recognize that team functioning and knowledge recombination in diverse teams entail costs (Taylor and Greve, 2006). Indeed, experience diversity implies communication and coordination costs since team members are required to collaborate with dissimilar others (Dougherty, 1992; Williams and O'Reilly, 1998). For instance, diverse teams find it more difficult to communicate ideas amongst each other, as they possess different types of background knowledge and are likely to use different types of jargon to explain their insights.

Furthermore, research tells us that diverse teams may face higher communication and coordination costs because they lack intra-group trust due to low social integration and pronounced intra-group task conflict (Richard, Murthi and Ismail, 2007). While these costs are likely to be small for low levels of team experience diversity, they increase as experience diversity increases. This is because when one experience field is added to the range of fields y that a team of size x already covers, the number of experience field combinations rises to $x*(y+1)$, thus increasing intra-group communication and coordination costs.

As noted earlier, existing empirical research indicates that these costs do not have a first-order effect on team performance in "average" settings. Indeed, the meta-analysis by Horwitz and Horwitz (2007) indicates a *positive* relationship between the task-related experience diversity of teams and their performance. In contrast to this result, we argue that the costs associated with team experience diversity do affect team performance in important ways, in hypercompetition. This is because diverse teams experience major difficulties in performing their tasks in the seamless and highly coordinated manner that is required to achieve timely advances in settings characterized by uncertainty and severe time pressures (Bechky and Okhuysen, 2011). Specifically, the uncertainty and time pressure teams face in hypercompetition significantly increase the stress experienced by team members and, thus, the likelihood and extent of intra-group task conflict and communication problems. For instance, when different viewpoints arise, which per se is more likely in diverse teams, these teams cannot discuss each viewpoint in depth and properly value each team member's contribution, as they feel the strong pressure to come up with a quick solution. Team members whose ideas are rejected without any proper explanation may continue to insist on their solution, turn passive, or even undermine the efforts of the team by seeking to build team-internal coalitions and escalating the latent conflict. Hence, compared to less challenging settings, these teams are likely to experience not only more conflict but also more intense conflict. As a result, they are likely to face difficulties in reaching agreements, which is particularly deleterious when quick decision making is vital to performance. In the worst case, they may not reach agreement at all and, as a consequence, they may either hold to an existing inferior solution or implement a novel solution that could be flawed.

In sum, we posit that beyond a certain level of team experience diversity the costs of such a set-up offset the related benefits, making the relationship between team experience diversity and team performance an inverted U-shape. Hence, we propose:

> *Hypothesis 1: In hypercompetitive environments, there exists an inverted U-shaped relationship between the level of experience diversity in R&D teams and their performance.*

Boundary conditions: R&D teams and their organizational context

Teams do not work in a vacuum but critically rely on their organizational context (Miner *et al*., 2001; Baker and Nelson, 2005; Joshi and Roh, 2009; Bechky and Okhuysen, 2011). Building on the conclusions derived in the previous section, we investigate how two organizational-level boundary conditions shape the relationship between R&D teams' experience diversity and their performance. These two conditions are the size and age of the firms with which these R&D teams are associated. Firm size and age have long been recognized as fundamental factors in prior work on organizational structure and innovation (e.g., Stinchcombe, 1965; Kimberly, 1976; Haveman, 1992; Haveman, 1993; Zenger, 1994, Zenger and Lazzarini, 2004). Firms of varying size and age are characterized by substantially different material, cognitive, and social resources, including the firms' knowledge endowments, routines, as well as search strategies (Cyert and March, 1963; Nelson and Winter, 1982). Thus, we expect both firm size and age to importantly affect the functioning of R&D teams operating under extreme conditions.

Paraphrasing Haans *et al.* (2015), these firm characteristics affect the latent mechanisms driving the inverted U-shaped relationship between teams' experience diversity and their performance by shifting the inflection point of the curve. To illustrate this point, suppose that the performance of an R&D team, *Y,* is a concave function of the level of R&D team experience diversity, X: $Y=\alpha_0 X-\alpha_1 X^2$. $\alpha_0 X$ are the benefits of R&D team experience diversity, while $\alpha_1 X^2$ are the costs. We are interested in the moderating effect of firm size or age, Z, on the relationship between R&D teams' experience diversity and their performance. To investigate this effect, we adopt a standard approach (Haans *et al.*, 2015) and increase the linear benefits of R&D team experience diversity by $\alpha_2 XZ$ and the convex costs by $\alpha_3 X^2 Z$. The inflection point of the inverted U-shaped curve occurs at $X^*=(\alpha_0+\alpha_2 Z)/(2*(\alpha_1+\alpha_3 Z))$, where $\alpha_0+\alpha_2 Z$ is the marginal benefit of increasing R&D team experience diversity and $\alpha_1+\alpha_3 Z$ the effect of increasing R&D team experience diversity on the marginal costs. At this point it becomes clear that the inflection point of the U-shaped curve shifts to the right or to the left, depending on whether or not Z magnifies the benefits of R&D team experience diversity more than the marginal cost.

Organizational size: Small versus large firms

Existing literature has highlighted both the advantages and disadvantages associated with large firm size (Cyert and March, 1963; Damanpour, 1996; Haveman, 1993). Specifically, firm size is considered to affect innovation positively because large firms have more resources available than small firms, which allow their R&D teams to adapt more easily to changing circumstances, undertake a large number of R&D projects and experiment with risky R&D projects (Damanpour, 1996; Haveman, 1993). Additionally, R&D teams in large firms can draw on a broad knowledge base and a "well-equipped" toolbox to facilitate the timely re-combination of existing knowledge and experience (Cohen and Levinthal, 1990). Based on these arguments, we should expect firm size to magnify the benefits of R&D teams' experience diversity.

Firm size may also magnify the potential costs inherent to R&D team experience diversity. This is because large firms are characterized by high levels of structural complexity and bureaucracy (Blau, 1970), slow responsiveness to change (Haveman, 1993), as well as payment schemes that poorly reward employees' effort (Zenger, 1994; Zenger and Lazzarini, 2004). Furthermore, in large firms, communication within and across teams requires complex and costly paradigms, assumes impersonal and formal tones, and creates differentiation of authority (Haveman, 1993). Altogether, these factors can hinder the innovation process and thus the performance of R&D teams (Aldrich and Auster, 1986; Camison-Zornoza *et al*., 2004).

In hypercompetitive environments, we expect the magnification of the positive effects of R&D teams' experience diversity caused by firm size to be first order with respect to cost amplification. In fact, in these environments, the greater availability of material, cognitive, and social resources is of fundamental importance for diverse R&D teams as they enhance and facilitate the ideation process, the rapid development of R&D projects, and provide these teams with key advantages when dealing with the high uncertainty characterizing their innovative projects. For instance, because of the richer and more stimulating setting offered by large firms, diverse teams are not only able to generate a greater number of solutions, as well as more varied solutions within a given project, but can also quickly execute a higher number of projects (cf. Bechky and Okhuysen, 2011), generate multiple real options and, thus, better leverage the risks associated with their innovation activities (Mohr, 1969; Ettlie and Rubenstein, 1987). Additionally, resource availability allows diverse R&D teams employed by large firms in hypercompetitive environments to react more quickly to shifts in environmental demands (Haveman, 1993).

Based on these arguments, we propose:

> *Hypothesis 2: In hypercompetitive environments, firm size moderates the inverted U-shaped relationship between R&D teams' experience diversity and their performance in such a way that the inflection point of the inverted U-shaped curve will occur earlier for teams working in small firms than for teams working in large firms.*

Organizational age: Young versus old firms

Similar to firm size, firm age has a fundamental impact on the accomplishment of tasks within organizations (Freeman, Carroll and Hannan, 1983; Sorenson and Stuart, 2000) and has potentially both functional and dysfunctional effects on the organization of R&D teams. A number of scholars have pointed out that, as firms become older, they accumulate valuable experience that allows them to efficiently pursue innovative projects, increase the reliability of their routines as well as external ties, and deepen their absorptive capacity (March, 1991; Sorenson and Stuart, 2000; Cohen and Levinthal, 1990). Moreover, as firms become older, they improve their capacity to evaluate competitors' innovative activities, which ultimately strengthens their competitive advantage (Leiblein and Madsen, 2008). Nevertheless, firm age is also associated with greater structural inertia in organizations, local searches for solutions, and low adaptation to environmental changes (Freeman *et al*., 1983; Aldrich and Auster, 1986; Kelly and Amburgey, 1991). Furthermore, old firms are often resistant to competency-destroying innovations (Tushman and Anderson, 1986; Tripsas, 1997).

The arguments just discussed suggest that firm age could positively affect both the benefits and costs of R&D teams' experience diversity. However, in hypercompetitive settings, the benefits should be more pronounced than the costs. Indeed, prior research tells us that organizations build up troves of supplies over time that can facilitate the creative actions of diverse teams, as they can quickly draw on these accumulated stocks of existing material, social, and cognitive resources when responding to dynamic changes in the competitive environment (Bigley and Roberts, 2001; Miner *et al*., 2001; Bechky and Okhuysen, 2011). However, we believe that the competitive pressures to which the organization finds itself subjected will mitigate any resistance to competency-destroying innovations that characterizes the R&D work of diverse teams in older firms. In fact, while older firms may, in general, find it relatively more beneficial to preserve the *status quo* rather than to experiment with major innovations (Methé, Swaminathan and Mitchell, 1996), they are likely to realize that they may have no other choice than to engage in frequent innovation in order to survive and prosper in hypercompetition.

Taken together, these arguments suggest that, holding firm size constant, firm age increases the benefits that can be derived from team experience diversity[3]. We thus posit that the inflection point of the inverted U-shaped curve representing R&D teams' performance as a function of their experience diversity should shift to the right for old firms (Haans *et al*., 2015).

> *Hypothesis 3: In hypercompetitive environments*, *firm age moderates the inverted U-shaped relationship between R&D teams' experience diversity and their performance in such a way that the inflection point of the inverted U-shaped curve will occur earlier for teams working in young firms than for teams working in old firms.*

METHODS

Empirical setting: the F1 motorsport industry

To test our hypotheses, we use data from F1 motorsport. F1 is one of the oldest race car series in existence and shares key features with the American IndyCar Series. The F1 series is governed by the Fédération Internationale de l'Automobile (FIA) and ranks among the most popular sports around the world, generating yearly revenues of 4.4 billion USD. Grand Prix races are held at different locations worldwide on purpose-built racetracks (circuits) as well as on public roads (Jenkins, 2004; Sylt and Reid, 2010). According to FIA regulations, car constructors must build their race cars' chassis. This requirement distinguishes F1 from other race series, such as the American IndyCar Series, where constructors may buy the chassis of their race cars. Within F1, constructors like Ferrari, McLaren, or Williams have their R&D teams design, and manufacture highly specialized single-seater, open-wheel cars. Constructors are typically medium-sized companies located in Europe, mainly in the region around Oxford, in the United Kingdom. Each constructor is allowed to compete with two cars and manages considerable budgets of up to 415 million USD. The F1 motorsport industry is considered a highly innovative industry at the forefront of technological development in car manufacturing.

[3] Referring to the simple mathematical example above, our statement implies that the coefficient α_2 in $X^*=(\alpha_0+\alpha_2 Z)/(\alpha_1+\alpha_3 Z)$ is positive, where Z is firm age.

Advancements in technology, highly dynamic regulatory environments, and knowledge leakage require constructors' R&D teams to innovate at a rapid pace to improve F1 cars' performance.

The R&D division of an F1 constructor consists of fifteen to eighteen engineers and is typically headed by three lead engineers: the Technical Director, the Chief Designer, and the Chief Aerodynamicist[4]. In line with prior research (e.g., work on upper echelons (cf. Hambrick and Mason, 1984) and dominant coalitions (cf. Cyert and March, 1963)), our analysis focuses on the top-level R&D team (henceforth: R&D team) that is composed of these three lead engineers, as they are responsible for making the key decisions in race car construction. In fact, race car performance is highly dependent on the efforts of these R&D teams (Grand Prix, 1992, 1997), as they organize the R&D work and have to ensure that different components of a race car fit together in a highly precise manner. Within an R&D team, each of the three lead engineers specializes in different task sets. The Technical Director is the head of the R&D division and oversees the development and deployment of race cars. He is responsible for the overall functioning of the race cars and must ensure that the resulting products fit the drivers' characteristics. The Chief Designer is responsible for the basic design of the race cars, chooses the materials, and plays a fundamental role in transforming components with potentially conflicting requirements into a unique and competitive final product. The Chief Aerodynamicist heads the aerodynamics division. Aerodynamics must create the downforce that keeps the race cars on the track and permits greater cornering speeds. The Chief Aerodynamicist not only manages this process but he must also minimize the air drag that is responsible for reducing the cars' speed. Each F1 R&D team is headed by a Team Principal. He is the constructor's CEO and is responsible for every management decision, including contracting sponsors and suppliers, recruiting drivers and engineers, as well as determining

[4] In case of *works teams* (i.e., constructors that build their cars' engines in addition to the chassis), the R&D team also includes a Chief Engine Designer. As the focus of our analysis is on the construction of a car's chassis and not on engine construction, we do not consider Chief Engine Designers. However, to differentiate *works teams* from the remainder, we control for *works teams* in our regressions.

wages. Although the Team Principal is not responsible for the cars' construction, he has the final say in all strategic decisions. We thus control for his background, as discussed below.[5]

Sample and data collection

Our analysis is based on unique, fine-grained data on F1 R&D teams, including their performance and a large number of additional key characteristics. Because this data is not available from a single source, we engaged in a comprehensive data collection effort that combined several electronic and paper-based sources. Specifically, we extracted information about R&D teams' composition and their race cars from the *www.motorsportarchiv.de* website. Moreover, we gathered Team Principals' biographical information from the F1 yearbooks and extensive internet searches.[6] Additionally, we collected data on qualifying classifications from the electronic database available at *www.motorsport-total.com*. We supplemented these data with information retrieved from the lead engineers' biographies, gathered once again through extensive internet searches. Finally, we extracted information on constructors' budgets from the F1 yearbooks, for the years 1993 to 2006, and from the F1 financial reports, for the years 2007 and 2008 (Sylt and Reid, 2008, 2009).

Our data set is constructed at the level of an F1 R&D team. Overall, the data set includes 88 R&D teams that operated from 1993 to 2008. During this period, these teams built a total of 141 race cars, with an average of 1.8 cars per team. For these cars, we observe 2,375 qualifying outcomes in F1 World Championship races. The R&D teams were employed by 13 F1 constructors and managed by 32 Team Principals. The average team tenure is 1.8 years, with a minimum of 1 year and a maximum of 7 years.

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[5] In a few cases, the R&D team is made up of only two lead engineers. These cases are mainly confined to the early years, when the Chief Aerodynamicist was not always included in an R&D team. Since the 1980s, these teams have systematically studied the aerodynamic properties, that is, after Colin Chapman had invented the *ground effect*. This invention subsequently led to the creation of the role of the Chief Aerodynamicist, which then, progressively, became part of an R&D team. There are also cases in which a team is made up of four lead engineers. This team set-up is typically observed either when a constructor wants to ensure a smooth transition from one Chief Designer to another, or when the CEO believes that the tasks of a Chief Designer are more efficiently performed by two employees. The latter case is more frequent for large constructors.

[6] For this purpose, we consulted a number of websites, such as LinkedIn and Wikipedia.

Measures

Dependent variable: R&D team performance

The speed of an F1 race car is key to race performance, which strongly depends on the R&D teams' work. For this reason, we operationalize R&D teams' performance using the percentage deviation of their cars' qualifying time from that of the fastest car during the qualifying session. Qualifying sessions take place on the day preceding a Grand Prix race. During these sessions, each driver has a number of trials to determine the grid position of his car during the race the following day. Because there are significant advantages in starting a race at the head of the grid, F1 drivers compete fiercely for this pole position. To facilitate the interpretation of the dependent variable, we multiply the ratio in (1) by the negative of 1. In this way, higher values of the dependent variable indicate better R&D team performance. Our dependent variable of interest, *R&D team performance*, is thus defined as:

$$R\&D\ team\ performance_{ij} = -\left(\frac{q_{ij} - q_{pole\ j}}{q_{pole\ j}}\right) \tag{1}$$

where $q_{pole\,j}$ refers to the qualifying time of the fastest car at qualifying session j and q_{ij} to driver i's qualifying time. As argued by Bothner, Kim, and Smith (2012), a car's qualifying time during the pre-race knockout session provides a better indication of R&D team performance than the time scored during an actual race, for two main reasons. First, during the qualifying sessions, competing cars are not allowed to block each other. Thus, their resulting score depends more on each car's technical performance, which ultimately relies on the R&D team, than on the driver's strategies. Second, contrary to race outcomes, qualifying results are not affected by accidents and other factors, such as refueling or changing tires, which are not directly related to the performance of R&D teams. As mentioned earlier, each constructor is allowed to enter two cars in a Grand Prix race. Because each car's qualifying outcome can be affected by the driver's errors, which are independent of an R&D team's accomplishment, we only consider the qualifying result of the faster of the two race cars.

Independent variable of interest: Experience diversity of R&D teams

Through extensive examination of the R&D team members' curricula and relevant F1 literature, we identified five major areas in which R&D teams have gathered task-related experience: *i*) industries other than motorsports, *ii*) Championship Auto Racing Teams (CART) sport, *iii*) Formulas other than F1 (e.g., Formula 2, GP2 Series, Formula 3000), *iv*) F1 constructors other than the current one, and *v*) race car building for non-commercial events.

Experience gathered *in industries other than motorsports* is instrumental to R&D team engineers in creating networks of suppliers and other partners. To cite an example, prior to joining F1, Rory Byrne, a star engineer at Benetton and Ferrari, worked as chief chemist at a polymer manufacturing plant. He then set up a company importing performance car parts. He cites these two work experiences as being instrumental for his later F1 position (Grandprix, 1996).

Experience in *CART sport*, which is a stepping stone to the higher and more expensive motorsport series, enables the engineers to understand their cars' fundamental physical principles. This is because CART sports cars are made of materials that are heavy and inflexible and, thus, difficult to handle. Experience in CART sport also makes engineers aware of the various F1-relevant parameters, like tire pressure, gearing, seat position, and chassis stiffness.

Experience in *other Formulas* allows engineers to improve the speed and reliability of their race cars and deal with the standardization of their cars' chassis.

Experience with *different F1 constructors* allows engineers to draw on their prior employers' knowledge when constructing new race cars. For example, Niccolo Petrucci, Chief Aerodynamicist at Toro Rosso, mentioned that in determining the aerodynamic properties of the "Toro Rosso STR 6" car, he drew from experience gained at Ferrari F1 in 1992 (F1 Technical, 2011).

Finally, car construction for *non-commercial events* helps an engineer to understand how to combine different car components and deal with budget constraints. Adrian Newey, an

F1 star designer, points out that his experience in race car construction for non-commercial events was key to learning how to improve a car's speed (Grandprix, 2013).

Based on the five aforementioned areas, we constructed our focal *Team experience diversity* measure as a Herfindahl Index (HI), defined as the sum, across experience fields $z=1,\dots,N$, of the square of the share (s_z) of R&D team members who have experience in a given field z. Hence:

$$\text{HI} = \sum_{z=1}^{N} s_z^2 \tag{2}$$

Moderators

Constructor size. We follow prior literature (see, for instance, Graves and Langowitz, 1993) and proxy this measure by the annual budget (in constant USD) that is available to constructors for paying for drivers, engineers and support staff, chassis, tires, fuel, transportation, logistics, as well as public relations. For the sake of comparison, we exclude engine expenditures from the constructor budget.

Constructor age. This measure captures the age of the constructor, which is defined as the number of years elapsed from foundation.

Control variables

Given the richness of our data set, we are able to control for a large number of team and organizational level characteristics that are likely to influence R&D team performance.

Team size. Team size is typically used as a proxy for the human capital available to a team, which, in our context, is likely to be a source of positive correlation between team experience diversity and performance (Bantel and Jackson, 1989; Wiersema and Bantel, 1992). Since team size in our empirical context can only take values of two, three, and four, we control for R&D team size by using three dummy variables flagging teams of two, three, and four members.

Team tenure. The longer team members have worked together, the lower their communication and coordination costs (Dixon, 1999; Bechky and Okhuysen, 2011). Additionally, as Bermann, Down and Hill (2002: 16) pointed out, high turnover in teams may "disrupt the ability of members to draw upon experientially constructed schemata in order to operate in a synchronous fashion". Following prior work (Taylor and Greve, 2006), we control for team tenure and we operationalize it as the count of F1 seasons during which the composition of a given team remained unchanged.

Team experience in F1. Since innovative output critically depends on the accumulation of prior experience (Ingram and Baum, 1997), we control for an R&D team's experience in F1. The measure is defined as the sum of the number of years each team member has worked in F1. We also include a squared term given that the impact of team experience on performance is likely to be characterized by diminishing returns (Finkelstein and Hambrick, 1996).

Team average age. This measure captures the average age of the team members, which is a proxy for their overall (not only F1) experience (Heckman and Robb, 1985).

Former productivity of the team members (non-F1). We use the share of team members who won a championship title in a race series other than F1 to control for team members' quality. The latter is likely to be a source of correlation between a team's performance and its diversity (Rigney, 2010).

Work experience Team Principal. We control for a Team Principal's experience given that he is responsible for all management decisions. We use three dummies, indicating whether the Team Principal had accumulated prior work experience as race engineer, race driver, or manager.

Change in drivers. The innovations implemented in a race car must be tailored to the characteristics of each driver. Becoming acquainted with driver characteristics entails a cost to the R&D team, which is lower if the drivers do not change from one season to another. We thus employ three dummy variables indicating whether an F1 constructor had kept both drivers, only one driver, or neither of the drivers, relative to the previous season.

Constructor type. We include a dummy that takes the value of 1 if a constructor builds both the cars' chassis and the engines (e.g., Ferrari) and a value of zero if it builds only the chassis (e.g., Williams). R&D teams working for the former have more freedom in constructing their race car (F1 Technical, 2005), which ultimately affects the cars' performance.

Constructor past success. To control for a constructor's quality, we include a dummy variable that controls for the constructor's past success. This dummy takes the value of 1 if the constructor was awarded the title of "Constructor World Champion" in any of the prior five years, and zero otherwise.

Driver past success. To control for a driver's quality, we use a dummy variable that takes the value of 1 if a driver won at least one F1 Driver World Championship, and zero otherwise.

Racetrack. Track characteristics are likely to affect qualifying outcomes. Indeed, there are some cars that are better equipped for city tracks, like Monaco, and others that perform better on purpose-built racetracks, like Silverstone. Typically, cars with higher top speed or cars with good aerodynamic properties perform better on purpose-built racetracks. A dummy variable thus controls for racetrack characteristics and takes the value of 1 for city tracks and zero for purpose-built tracks.

Weather. Race cars and their drivers cope differently with weather conditions. We thus include a dummy to control for weather conditions (1= rain, zero= other conditions).

Race of the season. To control for the race of a season, we employ a count variable that takes the value of 1 if a car is competing in the qualifying of a season's first race, 2 in the second qualifying, and so forth until the last season's qualifying. This measure controls for economies of learning that R&D teams gain over a season.

Season fixed effects. We include season fixed effects to control for season-specific factors that may affect qualifying outcomes.

Econometric methodology

We estimate the relationship between R&D teams' experience diversity and their performance with the following equation:

$$R\&D\ team\ performance_{ij} = \gamma_0 + \gamma_1 Team\ experience\ diversity_{ij} + \qquad (3)$$

$$+\gamma_2 Team\ experience\ diversity_{ij}^2 + x_{ij}'\beta + \varepsilon_{ij}$$

where the subscript *i* refers to a constructor's R&D team and the subscript *j* refers to a qualifying session. To test Hypothesis 1 regarding the inverse U-shaped relationship between a team's experience diversity and the resulting performance, we add the squared term of *Team experience diversity*. The vector x_{ij} contains the regressors described in the moderators and control variables section.

Verifying that the coefficient of *Team experience diversity* is positive and the squared term is negative, and that they are jointly significant, is necessary but not sufficient to test Hypothesis 1 (Aiken and West, 1991; Cardinal, Miller, and Palich, 2011). We must also verify that the slope of the curve describing the relationship between a team's experience diversity and its performance is "sufficiently steep at both ends of the data range" and has the expected sign in each range (Haans *et al.*, 2015: p. 6). Say $Team\ experience\ diversity_L$ is the low and $Team\ experience\ diversity_H$ is the high end of the data range, the slope of the curve at $Team\ experience\ diversity_L$, i.e. $\gamma_1 + 2\gamma_2 * Team\ experience\ diversity_L$, must be positive and significant, whereas the slope at $Team\ experience\ diversity_H$, i.e., $\gamma_1 + 2\gamma_2 * Team\ experience\ diversity_H$, must be negative and significant (Haans *et al.*, 2015). We discuss these tests in the results section.

Despite the fact that our data are rich in observed characteristics, we cannot completely rule out that there may be omitted factors that affect both an R&D team's experience diversity and its performance. Moreover, it is also possible that the estimates from equation (3) are biased by reverse causality (Hamilton and Nickerson, 2003). In fact, while we should expect that R&D team experience diversity affects a team's performance, it is also plausible that expected performance induces a constructor to decide on a given team composition. To address these concerns, we re-estimate equation (3) limiting the sample to races that occurred during the following years: 1994, 1998, 2001, 2004, 2005, 2006, and 2008. These years are characterized by profound changes in the rules governing F1 races.[7] Because these changes are unpredictable, we can assume that our focal independent variable, *Team experience diversity*, is uncorrelated with the error term in the aforementioned years.

As a robustness test, we estimate an instrumental variable (IV) model in which we instrument *Team experience diversity* and its squared term with plausibly exogenous regressors. We use as instruments the share of an R&D team's lead engineers for whom English is their mother tongue, the share of lead engineers for whom French is their mother tongue, and the share of lead engineers for whom Italian is their mother tongue. Discussions with experts revealed that lead engineers who work for British, French, and Italian F1 R&D teams have distinctive characteristics, which leads us to consider them as belonging to a British, French, or Italian "School". Conditional on our rich set of controls, these instruments should affect R&D teams' performance only through our *Team experience diversity*. We label the instruments as *Share EN*, *Share FR*, and *Share IT*. We include the squared terms of these shares to take into account non-linearities in the relationship between these shares and *Team experience diversity.* As a last instrument, we use the industry average of *Team experience diversity*. Having controlled for constructor and season characteristics, the identifying assumption, here, is that

[7] Specifically, in 1994 driver aids were banned. In 1998, a car's standard width was reduced and grooved tires became mandatory. In 2001, traction control was allowed. In 2004, the FIA established the minimum size of rear wing end plates. In 2005, the diffusion size was reduced and drivers were not allowed to change tires during a race. In 2006, tire changes were reintroduced. In 2008, traction control was banned.

the industry averages pick up the effects of industry-specific attributes that are uncorrelated with omitted R&D team-specific factors.

To test Hypothesis 2 regarding the moderating effect of firm size, we modify the equation specification in (3) and introduce interaction terms between the size of a constructor and both the linear and the squared term of *Team experience diversity*:

$$\begin{aligned} R\&D\ team\ performance_{ij} = {} & \gamma_0 + \gamma_1 Team\ experience\ diversity_{ij} \\ & + \gamma_2 Team\ experience\ diversity_{ij}^2 + \gamma_3 Team\ experience\ diversity_{ij} \\ & * Constructor\ size + \gamma_4 Team\ experience\ diversity_{ij}^2 * Constructor\ size \\ & + \gamma_5 Constructor\ size + z_{ij}'\beta + \varepsilon_{ij} \end{aligned} \tag{4}$$

where the vector z_{ij} contains the regressors described in the control variables section with the exception of a constructor's size.

In case we find support for Hypothesis 1, Hypothesis 2 predicts that firm size moderates the inverted U-shaped relationship between R&D teams' experience diversity and their performance in such a way that the inflection point of the inverted U-shaped curve will occur later (earlier) for teams employed by large (small) firms. By introducing the interaction terms between the size of a constructor and both the linear and the squared terms of *Team experience diversity*, the optimal value of *Team experience diversity,* at which the inflection point occurs, becomes:

$$Team\ experience\ diversity^* = \frac{-\gamma_1 - \gamma_3 * Constructor\ size}{2\gamma_2 + 2\gamma_4 * Constructor\ size} \tag{5}$$

A formal test of Hypothesis 2 thus requires that the derivative of *Team experience diversity** with respect to constructor size be positive:

$$\frac{\delta\ Team\ experience\ diversity^*}{\delta\ Constructor\ size} = \frac{\gamma_1\gamma_4 - \gamma_2\gamma_3}{2(\gamma_2 + \gamma_4 * Constructor\ size)^2} \tag{6}$$

Since the denominator of equation (6) is strictly greater than zero, Hypothesis 2 is supported if the numerator of equation (6) is greater than zero.

We test Hypothesis 3 regarding the moderating effect of firm age in a similar way as we do for Hypothesis 2. Specifically, we introduce in equation (3) interaction terms between the age of a constructor and both the linear and the squared term of *Team experience diversity*. Hypothesis 3 predicts that firm age moderates the inverted U-shaped relationship between R&D teams' experience diversity and their performance in such a way that the inflection point of the inverted U-shaped curve will occur later (earlier) for teams working in old (young) firms. To test this hypothesis, we introduce the interaction terms between the age of a constructor and both the linear and the squared terms of *Team experience diversity*. We then test whether the derivative of *Team experience diversity** with respect to firm age is positive.

RESULTS

Descriptive results

Tables 1 and 2 report summary statistics and correlations between the dependent and the explanatory variables used in the multivariate analysis. Table 2 indicates that correlations are relatively low, suggesting that multicollinearity is not a major concern. This intuition is formally confirmed by the estimation of variance inflation factors, which range between 1.02 and 3.41 and are thus below the critical value of 10.

Table 1 reports that 16 percent of the R&D teams are constituted of four lead engineers, 62 percent are made of three lead engineers, and the remaining 22 percent consist of two lead engineers. On average, an R&D team has accumulated 40 years of experience in F1, with a minimum of eight and a maximum of 68 years. The average size of a constructor, proxied by its budget, is 77 million of constant USD. The average constructor age, as of 2008, is 24 years.

Please insert Tables 1 and 2 about here

Figure 1 shows the distribution of the R&D team performance variable. The median value of this variable is -2.2, and the minimum and maximum values are -32 and 0, respectively, indicating that the distribution is skewed to the right.[8] This is not surprising; in fact, small improvements in the R&D teams' performance, measured by the percentage deviation of their cars' qualifying time from that of the fastest car during the qualifying session, make a large difference in terms of their cars' starting position in the Grand Prix race. For instance, at the 1997 French Grand Prix, the Benetton Renault B197, driven by Alexander Wurz, would have started from the pole position rather than starting from position 7, had it scored 0.5 percentage points higher in the qualifying session. Figure 2 illustrates the distribution of the *Team experience diversity* index. The variable's mean is 0.76, with a minimum value of 0.35 and a maximum value of 0.98. The distribution of *Team experience diversity* is skewed to the left, indicating that R&D teams in our study context tend to have high levels of experience diversity.

Please insert Figures 1 and 2 about here

Multivariate analysis

Table 3 presents the regressions results for the performance of a constructor's fastest car as a function of the level of its R&D team experience diversity and controls. We follow Angrist and Pischke (2008) and bootstrap standard errors. We do not cluster standard errors at the level of the constructors since we do not have enough clusters (Angrist and Pischke, 2008).

Model 1 only includes moderators and controls. Model 2 contains the team experience diversity variables as well as moderators and controls. Model 3 restricts the sample to races that had taken place in years characterized by profound regulation changes, as explained in the methods section. Finally, Model 4 estimates the IV regression model.

Please insert Table 3 about here

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[8] To ensure that our results are not driven by outliers we run a number of robustness tests in which we excluded from the sample those observations whose absolute performance deviation from the pole time exceeded 10%. After applying this criterion, the results remain unchanged.

Examining the controls in Model 1, we find that, as expected, the size of an R&D team is positively correlated with its performance. Additionally, we observe a significant relationship between a team's level of F1 experience and its performance. In line with findings in the existing literature, team members', drivers', and constructors' past performance are all significantly and positively correlated with an R&D team's current performance. A similar positive correlation is found when we examine a constructor's size, which we proxy by its budget, suggesting that the availability of resources is key for an R&D team's performance (Herold *et al.*, 2006). R&D teams that work with the same drivers from one season to another perform better than those whose drivers change from one season to the next. Also, R&D team performance during the last races of a season is stronger than performance during the earlier races. These last two results indicate that economies of learning are important predictors of R&D team performance.

Hypothesis 1 predicts an inverted U-shaped relationship between the level of an R&D team's experience diversity and its performance. We test this hypothesis in Model 2, which adds to Model 1 the interest variables *Team experience diversity* and its squared term. Consistent with Hypothesis 1we find that the coefficients of *Team experience diversity* and its squared term are both statistically significant and have the expected signs. An F-test on the joint significance of the coefficients of the linear and squared terms of *Team experience diversity* rejects the null hypothesis that these coefficients are jointly equal to zero with a p-value of 0.00. Given the magnitude of the coefficients, the inflection point is found at a value of *Team experience diversity* equal to 0.64, and thus lies within the range of our focal variable.

As a robustness test, Model 3 shows the results of a regression model in which we restrict the sample to races that had taken place in years characterized by profound regulation changes. The sample size decreases from 2,375 to 1,022 observations. The coefficients of the linear and squared terms of *Team experience diversity* remain significant and have the expected sign. The magnitude of the coefficients increases relative to Model 2, but the inflection point is reached for a value of *Team Experience Diversity* (0.70) that is very similar to the value derived by estimating Model 2 (0.64).

Model 4 presents the results of the IV regressions, having instrumented *Team experience diversity* and its squared term using the following instruments: i) the share of R&D team lead engineers for whom English is their mother tongue, *ii*) the share of lead engineers for whom French is their mother tongue, *iii*) the share of lead engineers for whom Italian is their mother tongue, *iv*) the squared terms of the aforementioned instruments, and *v*) the industry average of *Team experience diversity*. Columns (a) and (b) of Model 4 present the first-stage results for *Team experience diversity* and its squared term, while column (c) presents the IV estimates. As shown, the instrument coefficients are highly significant.[9] Regarding the IV estimates, we find that *Team experience diversity* and its squared term continue to be statistically significant. The magnitude of the coefficients increases relative to Model 2 and this is consistent with the results obtained by restricting the sample to seasons with regulation changes (Model 3). The resulting inflection point occurs for a value of *Team experience diversity* equal to 0.63, which is very similar to the values we derived from the previous models.

As discussed, a formal test of Hypothesis 1 regarding the inverted U-shaped relationship between a team's experience diversity and its performance requires the coefficient of team experience diversity to be positive and significant at the low end of the data range, i.e., the range of data up to the optimal value of team experience diversity. Additionally, the coefficient must be negative and significant at the high end of the data range, i.e., the range of data beyond the optimal value of team experience diversity. In practice, we split the sample at the optimal value of team experience diversity. Regression results for each subsample are presented in Table 4. As shown, the coefficients of *Team experience diversity* are highly significant and exhibit the expected sign in each subsample. Overall, these results provide support for Hypothesis 1.

[9] We reject the null hypothesis that the instruments are weak using the Anderson-Rubin Wald test. The corresponding F-statistic is 15.85 (Anderson and Rubin 1949; Baum, Schaffer, and Stillman, 2007).

Please insert Table 4 about here

Extending this key finding, our next set of hypotheses examines whether the organizational context affects the extent to which R&D teams' performance can benefit from their experience diversity. To test Hypothesis 2 regarding the moderating effect of firm size, we flag large constructors by creating two alternative dummies. The first dummy takes the value of 1 for those constructors that are above the median of the constructor size distribution, and zero otherwise. The second dummy, which we use as a robustness test, takes the value of 1 for those constructors that are in the last quartile of the size distribution, and zero otherwise. As discussed, we then interact each dummy with *Team experience diversity* and its squared term and test whether the numerator of equation (6),$\gamma_1\gamma_4 - \gamma_2\gamma_3$, is significantly greater than zero. The results are presented in Table 5. As shown in Models 5 and 6, we find that $\gamma_1\gamma_4$ is significantly greater than $\gamma_2\gamma_3$, regardless of the size dummy we employ. Taken together, these results provide support for Hypothesis 2.[10]

Finally, to test Hypothesis 3, we repeat the same procedure as in the case of constructor size. The related results are reported in Models 7 and 8 of Table 5. This time, we can only reject the null hypothesis that $\gamma_1\gamma_4 - \gamma_2\gamma_3$ is equal to zero when we use as a cutoff for firm age its median value. We do not reject the null hypothesis that $\gamma_1\gamma_4 - \gamma_2\gamma_3$ is equal to zero when we use as a cutoff the 75th percentile of firm age. Hence, support for Hypothesis 3 is not as strong as support of Hypothesis 2. A reason for this result might be that for very old firms the positive

[10] Ideally, we would have performed the same tests by estimating an IV regression model or by limiting the sample to races that had taken place in years characterized by profound regulation changes. We refrain from performing these robustness checks for the following reasons. In the case of the IV regression model, we do not have sufficiently strong instruments for the interaction terms between each of the size dummies, on the one hand, and *Team Experience Diversity* and its squared term, on the other hand. In the case of the sample limited to years characterized by profound regulation changes, we unfortunately do not have sufficient variability in constructor size to be able to perform our tests.

effect of firm age on the benefits generated by R&D team diversity is offset by the negative effect that age might have in terms of increasing resistance to innovation.

Please insert Table 5 about here

DISCUSSION

By drawing on research that has investigated teams operating in extreme settings as well as prior work on innovation, this paper has examined how an R&D team's composition affects its performance outcomes in hypercompetition, and how variation in two primary organizational features – the size and the age of an organization – contextualizes this important relationship. Our analysis of a unique, longitudinal data set capturing 88 R&D teams in Formula 1 (1993-2008) produced two main findings: First, we found an inverse U-shaped relationship between the diversity in experience of R&D teams and team performance in hypercompetitive settings. Second, our results indicate that more diverse R&D teams operating in large organizations can draw greater benefits from their experience diversity than R&D teams working in small organizations, as the inflection point of the inverted U-shaped curve occurred later for teams in large firms than for those in smaller firms. The moderation effect of firm age while consistent with our hypotheses is not as robust as the effect of firm size. Taken together, these findings offer a number of novel theoretical implications for the strategy literature, and for related work on innovation and teams.

Theoretical Implications

Most generally, the present research contributes to the rapidly growing body of literature examining the antecedents to superior performance outcomes in hypercompetition (D'Aveni *et al*., 2010; McGrath, 2013). Notably, our study is the first in this literature to focus on the locus of the firm's inventive activity – the R&D team – and to develop and test new theory on how the composition of an R&D team affects its performance in hypercompetition. Importantly, our results show an inverted U-shaped relationship between the level of a team's task-related experience diversity and its performance in this extreme setting. This relationship stands in stark contrast to the leading contemporary opinion in the literature on teams, suggesting a positive relationship between team diversity in task-related experience and performance (i.e., "greater diversity is better") (cf. Horwitz and Horwitz, 2007). In other words, this means that extreme caution is necessary when applying the insights of well-established theories developed in the context of stable environments to hypercompetitive settings (D'Aveni *et al*., 2010; McGrath, 2013). Furthermore, this finding calls for a significant research agenda, as the boundary conditions of existing theories need to be investigated, and the development of new theories on the drivers of team performance in extreme settings will have to be pursued.

Along these lines our results also provide intriguing insights on how teams operating in extreme settings should best be composed in order to master the manifold challenges posed by these settings. Whereas studies on teams in extreme conditions have produced a number of interesting insights (Weick, 1993; Klein *et al*., 2006; Weick and Sutcliffe, 2007; Bechky and Okhuysen, 2011), our empirical investigation of R&D teams is able to add to this body of research by (i) shedding new light on how team composition affects its performance in extreme settings, and by (ii) explicitly considering how different organizational contexts affect teamwork in extreme settings. In particular, the latter results not only support Bechky and Okyhuysen's (2011) finding that the material, cognitive, and social resources offered by an organization enable (or constrain) teams in extreme settings, but reveal how the team's composition and the organizational context jointly shape outcomes in these settings.

The findings of this study also provide novel contributions for *innovation research* as well as the literature on *teams*. First, innovation analysts have observed that teams play an increasingly important role in the production of knowledge (Wuchty, Jones and Uzzi, 2007). We add new insights to this body of work by providing empirical evidence indicating how R&D teams can produce successful outcomes in highly competitive settings, i.e., settings that place particularly strong demands on teams' ability to innovate. Finally, our results provide new insights for the team literature. Because teams are not simply the sum of their parts but engage in collective problem-solving activities (Dixon, 1999), scholars have been intrigued by the question regarding how team composition affects outcomes in larger organizations (Finkelstein *et al*., 2009). We add to this body of knowledge in two ways – by showing that well-established relationships do not hold true for hypercompetitive settings, and by providing evidence of important contextual factors shaping the team diversity–performance relationship. In this regard, Joshi and Roh (2009) have called for more research examining organizational context variables in studies on team diversity.

Managerial Implications

By bringing people and organizational characteristics into research on hypercompetition, our study is able to offer actionable managerial implications. In particular, our findings indicate that the benefits and costs associated with team diversity depend in important ways on the organization's size. For instance, a CEO called to restructure a firm operating in a hypercompetitive environment will have to consider whether the firm they work for is small or large when setting the optimal level of R&D team experience diversity.

Limitations

When interpreting the results of this study, several limitations must be kept in mind. While our empirical setting offers several advantages for studying the relationship between R&D team composition and performance in hypercompetition, the question arises as to whether our results can be generalized to other settings. Despite this limitation, we note that the conditions encountered by R&D teams in the F1 motorsport industry are similar to those in other hypercompetitive industries, where the performance of teams largely depends on the ability to introduce innovative products within a short time span (McGrath, 2013). Examples of these industries include software, information, and communications, and less R&D-intensive industries, such as entertainment and fashion. Another limitation is that our setting is characterized by a small number of industry incumbents and is heavily regulated. While these features allowed us to collect detailed data on the entire F1 industry and utilize regulation shocks to identify the impact of team experience diversity on performance (Lengnick-Hall and Wolff, 1999), future research should extend our findings to hypercompetitive settings characterized by a greater number of firms and fewer regulations. Finally, although we were able to collect unusually fine-grained information for our sample teams, we must acknowledge certain limitations inherent in our data collection effort. Like many studies examining teams in organizations, we use demographic data (experience backgrounds) as a proxy for cognitive factors that are hard to observe in reality, especially when larger scale empirical evidence is sought (Dougherty, 1992; Hambrick and Mason, 1984). Also, the available data do not allow us to weigh our diversity measure by using the number of years that a team member had worked in a given field. In addition, we note that our data capture the upper echelons of R&D divisions. Even though these are key for generating innovations, it would be interesting to extend our research to the lower R&D team levels.

CONCLUSION

In a world where an increasing number of firms operate in hypercompetition, pinpointing the factors that shape the performance of teams affiliated with these firms is a core issue for strategy studies. As our results indicate, great caution is necessary when applying theories and concepts that were developed on the grounds of stable environments to hypercompetitive settings. We thus hope that our research will provide future studies with the critical information needed for a comprehensive understanding of the factors affecting R&D team performance in hypercompetition.

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TABLES AND FIGURES

TABLE 1 - Descriptive Statistics (N = 2,375)

Variable	Mean	Std. Dev.	Min	Max
R&D team performance	-2.31	1.84	-32.045	0
Team experience diversity	0.76	0.13	0.35	0.98
Constructor size [M USD]	0.77	0.57	0.05	2.15
Constructor age [years]	17.57	16.87	0	58
Team size = 2	0.22		0	1
Team size = 3	0.62		0	1
Team size = 4	0.16		0	1
Team experience	40.54	12.76	8	58
Team tenure	0.76	1.24	0	6
Team average age	42.72	3.51	32.33	49
Former productivity team members (non-F1)	0.14	0.21	0	0.67
Work experience Team Principal (TP):				
TP owner manager	0.31		0	1
TP former engineer	0.23		0	1
TP former driver	0.46		0	1
Change in drivers:				
Same drivers	0.31		0	1
One driver the same	0.48		0	1
No driver the same	0.20		0	1
Constructor type = works team	0.20		0	1
Constructor past success	0.21		0	1
Driver past success	0.13		0	1
Racetrack = city track	0.12		0	1
Weather = rainy weather	0.14		0	1
Race of the season	8.93	4.90	1	19

TABLE 2 - Correlations (N = 2,375)

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	R&D team performance	1																				
2	Team experience diversity	-0.10	1																			
3	Constructor size	0.44	-0.03	1																		
4	Constructor age	0.29	-0.18	0.35	1																	
5	Team size	0.18	-0.01	0.36	0.13	1																
6	Team experience	0.30	-0.12	0.54	0.45	0.66	1															
7	Team tenure	0.13	-0.03	0.05	0.19	-0.28	-0.01	1														
8	Team average age	0.18	-0.10	0.47	0.18	0.22	0.11	0.46	1													
9	Former prod. team	0.26	-0.04	0.31	0.37	0.10	0.08	0.27	0.27	1												
10	TP owner manager	-0.22	0.22	-0.43	-0.02	-0.19	0.06	-0.24	-0.21	-0.24	1											
11	TP former engineer	0.09	0.30	0.20	0.09	-0.24	0.13	-0.12	0.07	0.08	0.24	1										
12	TP former driver	0.05	-0.15	-0.09	-0.003	0.01	-0.07	0.11	-0.07	-0.04	0.07	-0.50	1									
13	Same drivers	0.23	-0.21	0.31	0.15	0.05	0.10	0.25	0.19	0.12	-0.30	0.03	-0.01	1								
14	One driver the same	-0.05	0.10	-0.12	-0.02	-0.04	-0.005	-0.12	-0.15	-0.12	0.19	0.02	-0.02	-0.65	1							
15	No driver the same	-0.20	0.12	-0.21	-0.15	-0.01	-0.11	-0.14	-0.03	0.01	0.11	-0.06	0.03	-0.34	-0.49	1						
16	Works team	0.29	-0.14	0.64	0.25	0.23	0.07	0.36	0.49	0.31	-0.64	-0.10	-0.08	0.28	-0.19	-0.08	1					
17	Constructor past success	0.35	-0.04	0.28	0.47	0.03	0.30	0.29	-0.01	0.24	-0.14	0.04	0.01	0.17	-0.05	-0.14	0.18	1				
18	Driver past success	0.28	-0.14	0.24	0.31	-0.003	0.09	0.14	0.11	0.34	-0.16	-0.04	0.08	0.17	-0.13	-0.04	0.27	0.30	1			
19	Racetrack	-0.07	-0.003	0.004	0.01	0.01	-0.002	0.01	-0.001	-0.004	0.001	-0.002	0.001	0.01	-0.002	-0.004	0.002	0.001	0.03	1		
20	Weather	-0.01	-0.02	-0.07	0.01	-0.03	0.01	-0.04	-0.04	0.02	0.05	-0.02	-0.01	-0.02	0.04	-0.02	-0.04	0.02	-0.01	-0.06	1	
21	Race of the season	0.08	0.01	0.04	-0.001	0.03	-0.01	0.03	0.03	-0.01	-0.03	0.01	-0.01	0.01	0.004	-0.01	0.02	-0.01	-0.04	-0.29	0.06	1

Note: 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

			Sample limited to race seasons with regulatory changes			
	OLS	OLS	OLS	IV (1st stage)	IV (1st stage)	IV
	Model 1	**Model 2**	**Model 3**		**Model 4**	
				(a) DV: Team experience diversity	**(b)** DV: Team experience diversity (sqr)	**(c)** DV: R&D team performance
		DV: R&D team performance				
Team experience diversity		10.162***	14.704***			12.929**
		[2.104]	[3.403]			[5.585]
Team experience diversity (sqr)		-7.923***	-10.558***			-10.292***
		[1.448]	[2.348]			[3.792]
F-test (joint significance)		F=53.90	F=21.20			chi2=50.69
		p=0.000	p=0.000			p=0.000
Inflection point		0.64	0.70			0.63
Constructor size [M USD]	1.054***	1.088***	0.960***	0.030***	0.047***	1.098***
	[0.122]	[0.114]	[0.233]	[0.005]	[0.007]	[0.118]
Constructor age [years]	-0.001	-0.002	0.008*	-0.0004***	-0.0004**	-0.003
	[0.002]	[0.002]	[0.004]	[0.0001]	[0.0002]	[0.003]
Team size = 3 (dummy)	0.259	0.161	0.300	0.036	-0.015	0.138
	[0.169]	[0.165]	[0.223]	[0.008]	[0.012]	[0.139]
Team size = 4 (dummy)	0.990***	0.866***	0.785***	0.049***	0.052***	0.842***
	[0.210]	[0.211]	[0.278]	[0.010]	[0.014]	[0.187]
Team experience	0.071***	0.066***	-0.018	0.007***	0.011***	0.064***
	[0.014]	[0.014]	[0.027]	[0.001]	[0.001]	[0.017]
Team experience (sqr)	-0.001***	-0.001***	-0.000	-0.0001***	-0.0001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Team tenure	0.034	0.008	-0.042	0.007***	0.007***	-0.001
	[0.029]	[0.027]	[0.062]	[0.001]	[0.002]	[0.031]
Team average age	-0.018	-0.023*	0.018	-0.007***	-0.009***	-0.026**
	[0.013]	[0.013]	[0.025]	[0.001]	[0.001]	[0.013]
Former productivity team members	1.213***	1.329***	1.018***	0.013	0.021	1.379***
	[0.166]	[0.170]	[0.316]	[0.012]	[0.016]	[0.199]
TP former engineer (dummy)	0.570***	0.625***	0.132	0.059***	0.081***	0.668***
	[0.124]	[0.136]	[0.206]	[0.005]	[0.008]	[0.122]
TP former driver (dummy)	0.499***	0.458***	0.132	0.012***	0.016***	0.445***
	[0.063]	[0.063]	[0.141]	[0.004]	[0.006]	[0.078]
Same drivers (dummy)	0.655***	0.541***	1.193***	-0.023***	-0.028***	0.485***
	[0.112]	[0.115]	[0.241]	[0.005]	[0.007]	[0.102]
One driver the same (dummy)	0.556***	0.516***	0.916***	0.014***	0.023***	0.499***
	[0.108]	[0.107]	[0.201]	[0.005]	[0.007]	[0.088]
Constructor type = works team (dummy)	0.075	0.036	0.100	-0.047***	-0.081***	0.028
	[0.121]	[0.130]	[0.252]	[0.006]	[0.008]	[0.123]
Constructor past success (dummy)	0.831***	0.776***	0.767***	0.025***	0.028***	0.767***
	[0.074]	[0.080]	[0.142]	[0.005]	[0.007]	[0.108]
Driver past success (dummy)	0.612***	0.544***	0.009	-0.001	-0.001	0.515***
	[0.092]	[0.091]	[0.143]	[0.005]	[0.007]	[0.104]
Racetrack = city track (dummy)	-0.352**	-0.351***	-0.591***	-0.0001	-0.0002	-0.351***
	[0.138]	[0.134]	[0.195]	[0.005]	[0.007]	[0.095]
Weather = rainy weather (dummy)	-0.076	-0.083	0.068	-0.010**	-0.014**	-0.086
	[0.085]	[0.080]	[0.155]	[0.004]	[0.006]	[0.089]
Race of the season	0.019***	0.019***	-0.002	0.0004	0.0005	0.019***
	[0.007]	[0.007]	[0.011]	[0.0003]	[0.0005]	[0.006]
Year dummies	included	included	included	included	included	included
Share language EN				-0.279***	-0.456***	
				[0.020]	[0.029]	
Share language EN (sqr)				0.123***	0.218***	
				[0.017]	[0.024]	
Share language IT				0.263***	0.363***	
				[0.028]	[0.040]	
Share language IT (sqr)				-0.455***	-0.558***	
				[0.056]	[0.081]	
Share language FR				-0.004	-0.069**	
				[0.024]	[0.033]	
Share language FR (sqr)				0.073**	0.198***	
				[0.032]	[0.041]	
Industry av. team experience diversity				-3.743***	-5.355***	
				[0.126]	[0.190]	
Constant	-5.438***	-8.022***	-9.193***	3.511***	4.496***	-8.511***
	[0.569]	[0.920]	[1.653]	[0.085]	[0.131]	[2.093]
Observations	2,375	2,375	1,022	2,375	2,375	2,375
R-squared	0.368	0.381	0.336	0.749	0.752	0.378

TABLE 4 - Multivariate Analysis – Test of Inverted U-Shaped Relationship

	Model 2		Model 3		Model 4	
	< MAX	> MAX	< MAX	> MAX	< MAX	> MAX
	Model 2a	**Model 2b**	**Model 3a**	**Model 3b**	**Model 4a**	**Model 4b**
	DV: R&D team performance					
Team experience diversity	90.851***	-1.774***	4.480***	-4.728***	88.538***	-4.034***
	[22.181]	[0.406]	[0.957]	[1.326]	[22.217]	[0.648]
Control variables	included	included	included	included	included	included
Constant	11.686	-3.240***	2.845	-2.458	9.797	-1.520*
	[15.939]	[0.583]	[2.262]	[2.634]	[17.586]	[0.795]
Observations	371	2,004	326	696	371	2,004
R-squared	0.714	0.347	0.616	0.268	0.714	0.338

Note: Standard errors are bootstrapped with 500 replications. They are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.
The notation “<MAX” refers to observations whose value of team experience diversity is below the one at which R&D team performance achieves its maximum. Similarly, “>MAX” refers to observations whose value of team experience is above the value at which R&D team performance achieves its maximum.

TABLE 5 - Multivariate Analysis – Test of Interaction Effects

	Firm size > median	Firm size > 75 percentile	Firm age > median	Firm age > 75 percentile
	Model 5	**Model 6**	**Model 7**	**Model 8**
		DV: R&D team performance		
Team experience diversity	6.176***	7.445***	19.272***	8.845***
	[2.335]	[2.124]	[3.550]	[3.054]
Team experience diversity (sqr)	-5.112***	-5.972***	-13.548***	-6.875***
	[1.604]	[1.453]	[2.402]	[2.050]
F-Test (joint significance)	F=17.84 p=0.000	F=29.39 p=0.000	F=35.12 p=0.000	F=22.89 p=0.000
Inflection point	0.60	0.62	0.71	0.65
Diversity * large constructor	10.603**	18.895***		
	[4.175]	[4.936]		
Diversity (sqr) * large constructor	-6.990**	-12.590***		
	[2.877]	[3.468]		
Large constructor (dummy)	-3.354**	-6.590***		
	[1.509]	[1.708]		
Diversity * old constructor			-10.893***	6.113
			[4.197]	[4.744]
Diversity (sqr) * old constructor			6.971**	-3.880
			[2.904]	[3.638]
Old constructor (dummy)			3.660**	-2.096
			[1.485]	[1.511]
γ1*γ4-γ2*γ3 (size)	11.036*	19.110**		
	[6.746]	[8.215]		
γ1*γ4-γ2*γ3 (age)			228.800**	-61.004
			[130.970]	[49.648]
Constructor size [M USD]			1.080***	0.934***
			[0.122]	[0.145]
Constructor age [years]	-0.001	-0.002		
	[0.003]	[0.003]		
Team size = 3 (dummy)	0.144	0.176	-0.073	0.089
	[0.185]	[0.176]	[0.171]	[0.191]
Team size = 4 (dummy)	0.946***	1.040***	0.565***	0.757***
	[0.211]	[0.203]	[0.198]	[0.216]
Team experience	0.058***	0.062***	0.058***	0.050***
	[0.017]	[0.018]	[0.015]	[0.018]
Team experience (sqr)	-0.001***	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]
Team tenure	0.065**	0.058**	0.094***	0.063**
	[0.027]	[0.027]	[0.026]	[0.028]
Team average age	-0.013	-0.001	-0.002	-0.006
	[0.013]	[0.013]	[0.013]	[0.013]
Former productivity team members	1.369***	1.404***	1.125***	1.168***
	[0.179]	[0.215]	[0.176]	[0.179]
TP former engineer (dummy)	0.735***	0.762***	0.481***	0.432***
	[0.123]	[0.149]	[0.130]	[0.128]
TP former driver (dummy)	0.493***	0.500***	0.389***	0.393***
	[0.075]	[0.069]	[0.066]	[0.067]
Same drivers (dummy)	0.607***	0.630***	0.356***	0.500***
	[0.110]	[0.129]	[0.110]	[0.111]
One driver the same (dummy)	0.513***	0.579***	0.360***	0.454***
	[0.104]	[0.115]	[0.103]	[0.109]
Constructor type = works team (dummy)	0.389***	0.524***	-0.148	0.034
	[0.104]	[0.106]	[0.130]	[0.162]
Constructor past success (dummy)	0.704***	0.938***	0.875***	0.665***
	[0.085]	[0.081]	[0.083]	[0.087]
Driver past success (dummy)	0.593***	0.553***	0.560***	0.490***
	[0.092]	[0.090]	[0.088]	[0.090]
Racetrack = city track (dummy)	-0.349**	-0.347**	-0.348**	-0.347**
	[0.150]	[0.137]	[0.139]	[0.137]
Weather = rainy weather (dummy)	-0.037	-0.036	-0.053	-0.059
	[0.087]	[0.080]	[0.080]	[0.083]
Race of the season	0.020***	0.020***	0.020***	0.020***
	[0.007]	[0.007]	[0.007]	[0.007]
Year dummies	included	included	included	included
Constant	-6.695***	-7.582***	-11.648***	-7.554***
	[1.041]	[0.940]	[1.367]	[1.260]
Observations	2,375	2,375	2,375	2,375
R-squared	0.341	0.331	0.361	0.352

Note: Standard errors are bootstrapped with 500 replications. They are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 1 - Distribution of R&D Team Performance (N = 2,375)

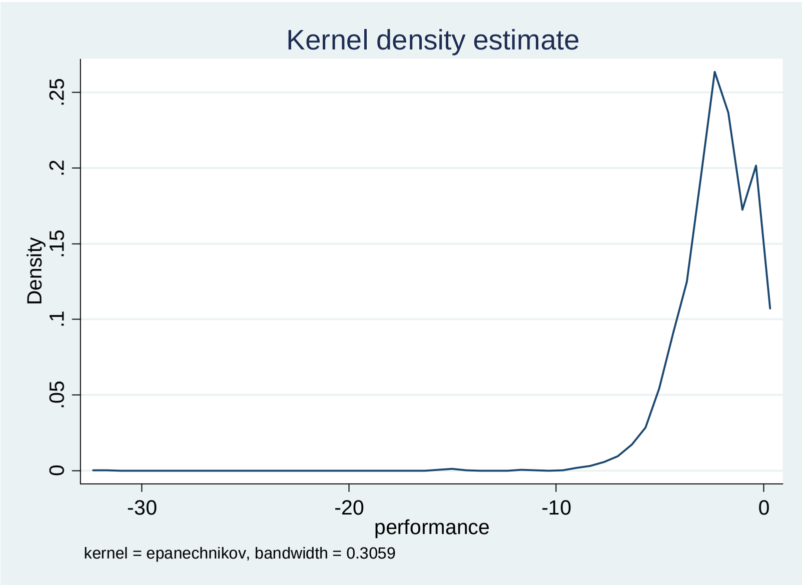

FIGURE 2 - Distribution of Team Experience Diversity (N = 2,375)