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# Decomposing profile-to-role configurations in R&D-focused entrepreneurial teams

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A B S T R A C T

We draw on social categorization theory to explain how entrepreneurial teams focused on research and development (R&D) are configured to deliver successful new venture performance. Research on entrepreneurial teams tends to aggregate individuals to the team level, which helps distill the effects of complementarities among social categories of team members. Specifically, we examine how scientists and managers apply their unique profiles (i.e., accumulated skills and expertise) to execute their respective roles within entrepreneurial teams engaged in commercial scientific discovery. In line with the entrepreneurial team literature, we distinguish between "focused" and "diversified" social categorizations of principal scientists and managers. As such, we differentiate between individuals' deep knowledge of a discipline and a background in two professional areas with relative expertise in each, likened to the "jack-of-all-trades". We analyze how team profile-to-role configurations might result in different new venture outcomes being R&D performance and commercial performance. To examine our models, we use multi-source, longitudinal, secondary data drawn from 153 government-funded research-intensive ventures associated with the National Cancer Institute in the United States (U.S.). Our results reveal differential effects for R&D performance and commercial performance. We find that teams aiming to enhance their R&D performance should seek diversified principal scientists, whereas teams seeking commercial gains should appoint diversified managers. By the same token, diversified team members may bypass their own shortcomings and complement their strengths by attracting team members with focused social categorizations.

## 1. Introduction

Technology-oriented new ventures are founded with the aim of exploiting their unique technological know-how and strong innovation competences. However, they vary significantly in their new product development (NPD) success (Shepherd et al., 2021). Most technology-oriented new ventures are founded and led by a small team, often two individuals (Colombo & Grilli, 2005; Davidsson & Honig, 2003; Ruef et al., 2003). This is particularly evident in complex and high-novelty contexts (Amason et al., 2006), such as in science-based technology markets. Entrepreneurial teams of small research-focused firms typically comprise an academic scientist who brings highly specialized knowledge and technological competences and a manager who possesses general and diverse competences and commercial experience (Ensley & Hmieleski, 2005). As such, akin to larger organizations in knowledge-driven industries, "entrepreneurial dyads" (Harper, 2008) focus on research and development (R&D) and encompass scientist and business roles (Berg, 2016; Katz et al., 1995; Mollick, 2012; Ter Wal et al., 2020).

This presents a fundamental issue regarding the composition of these entrepreneurial dyads. In theoretical terms, there is a stream of literature that argues for the "jack-of-all-trades" approach (Lazear, 2004), whereby start-up founders and their management team should be generalists. The broad skill set of generalists creates more novel ideas (Burt, 2004; Hargadon & Douglas, 2001), recognizes more opportunities (Gruber et al., 2012), and typically provides access to more resources at lower cost (Davidsson & Honig, 2003; Vissa, 2012). In contrast, other scholars criticize this breadth of experience to favor the focused experience of the specialist (Aldrich & Ruef, 2006; Leung & Sharkey, 2014; Zuckerman, Kim, Ukanwa, & Rittmann, 2003). This underlies an embryonic literature that seeks to reconcile these contradictions, with significant research by Kacperczyk & Younkin (2017) and Souitaris et al. (2022) among them.

In R&D-intensive scientific ventures, individuals in *scientist roles* are

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equipped with a primary task of generating innovative ideas and identifying technological opportunities to explore. On the other hand, team members in *business roles* are responsible for recognizing the "business case" (i.e., they evaluate which technological ideas fit with business opportunities and select the most promising ones for further development and commercialization) (Corbett, 2007; Ter Wal et al., 2020). Such division of labor within teams is intended to facilitate integration of unique individual-specific technological and market knowledge to achieve desired collective outcomes. Still, innovator and business roles are interdependent (Allen & Katz, 1992; Lingo & O'Mahony, 2010), particularly in newly founded firms (Jung et al., 2017), as some tasks may not be formalized and therefore call for team members' joint effort and interaction (Ter Wal et al., 2020).

Although extant studies suggest that both scientist's and manager's roles are central for venture success, the literature addressing the interdependence of scientific and managerial roles within entrepreneurial teams is currently underdeveloped. There are some exceptions to this in the broader literature such as Souitaris et al. (2022).

We draw on the human capital literature but specifically social categorization theory as an important lens through which to explain new venture performance managed by smaller entrepreneurial teams. A large body of literature has examined the effects of characteristics, diversity, heterogeneity, and composition of entrepreneurial teams, yet conclusions vary significantly with regard to the extent to which these characteristics affect new venture performance (Jin et al., 2017). Research on entrepreneurial teams tends to aggregate individual effects to the team level as if employees were a combined resource (Wright et al., 2001). However, little is known about how *individual* human capital embedded in key entrepreneurial team roles *interacts* to affect different forms of venture success (Unger et al., 2011). Our focus is to understand how scientists and managers apply their unique profiles (i.e., accumulated skills and expertise) to execute their respective roles within entrepreneurial teams. Specifically, we examine *whether various profile-to-role configurations within entrepreneurial R&D-focused teams lead to different performance outcomes.*

We address this research question by studying focused and diversified profiles as they reflect complex cognitive and knowledge resources of individuals, such as education and work experience that derive from social categorization. We explore how focused and diversified profiles are manifest in scientific and managerial roles within R&D-focused entrepreneurial teams. Specifically, we analyze whether two within-team configurations (diversified scientist and focused manager, and focused scientist and diversified manager), have differential effects on the R&D performance and commercial performance of the science-based entrepreneurial ventures. As such, we examine the question, *how should entrepreneurial teams be configured to achieve R&D versus commercial outcomes*?

We test the effects of profile-to-role configurations on entrepreneurial performance using multi-source data on a sample of 153 entrepreneurial project-teams that participated in the Small Business Innovation Research (SBIR) program in the United States over a seven-year period. The aims of the program are to encourage small businesses to explore their entrepreneurial potential, stimulating technological innovation and encouraging private-sector commercialization of the technology, product, or service arising from R&D activities. Therefore, the SBIR initiative represents a unique empirical context for testing which configurations of skills within entrepreneurial teams lead to R&D and commercial outcomes, as funded ventures are expected to perform in terms of innovation and commercialization (Wang et al., 2020).

This article makes several contributions. First, we use a more fine-grained approach to human capital by investigating the performance effects of different social categorizations or types of entrepreneurial team members' professional profiles. Second, the entrepreneurship literature has focused on understanding entrepreneurial team composition at an aggregate level but has relatively ignored the role of individuals in relation to the key roles represented on an entrepreneurial team. We add to this literature an investigation of profile-to-role configurations within a dyadic leadership team. Specifically, our results show how complex profiles of entrepreneurial team members (i.e. focused and diversified or otherwise described as specialist and generalist [Souitaris et al., 2022]) are exhibited in the roles of a principal scientist and a manager. Third, we investigate how unique configurations of these social categorizations within a team are differentially associated with different performance dimensions, such as commercial performance and R&D performance. We show that ventures have superior R&D versus commercial performance depending on whether focused or diversified profiles underpin scientific and managerial team roles.

## 2. Theoretical background

### 2.1. Social categorization theory in early-stage ventures

There is a tradition in the entrepreneurship literature that adopts a human capital lens to study phenomena. A positive association between human capital attributes and entrepreneurial success has long been established and explained through their role in discovering, accessing, and exploiting new entrepreneurial opportunities (Alvarez & Barney, 2007; Bruns et al., 2008; Marvel, 2013; Ucbasaran et al., 2008). Human capital also shapes cognitive perspectives and underpins the creation of new knowledge that enables nascent ventures to realize various benefits (Corbett et al., 2007).

Within the human capital literature, multiple manifestations of social categorization have been employed, including education, experience, knowledge, and skills. Recent reviews have demonstrated the theoretical and empirical importance of conceptually distinguishing between social categorization investments and social categorization outcomes (Horwitz & Horwitz, 2007; Marvel et al., 2016; Unger et al., 2011). Social categorization investments encompass acquired education and work experience that may or may not translate into knowledge and skills—direct outcomes of social categorization (Unger et al., 2011). There has been a call for more research exploring how social categorization investments and outcomes apply to milestones within the entrepreneurial process (Marvel et al., 2016). In line with prior studies, we use social categorization investments as "inputs" that make up unique professional profiles and explore their role in explaining entrepreneurial performance.

In assessing the success of science-based entrepreneurial ventures, it is important to acknowledge that such firms operate at the crossroads of research (where science is an end goal) and industry (where science is a means to achieve commercial goals) (Etzkowitz, 1998; Ndonzuau et al., 2002). We build on the concept of this form of social categorization (sometimes described as "profile differentiation") of team members, which is an attribute that helps science-based entrepreneurial teams facilitate the pursuit of research and business goals by having individuals with academic and non-academic profiles (Visintin & Pittino, 2014). In investigating how individual profiles relate to the roles of key entrepreneurial team members, we further distinguish between professional specialization and professional diversification—focused (i.e., academic) and diversified (i.e., academic-commercial) profiles.[1]

[1] The literature that examines entrepreneurial teams expresses these profiles in different ways. One of the most common approaches of social categorization are the *specialist* (Zuckerman, 2003; Leung, 2014; Leung and Sharkey, 2014) and *generalist* (Lazear, 2004; Kacperczyk and Younkin, 2017) profiles. We choose instead to adopt the nomenclature of the *focused* and *diversified* profiles in this study because these terms convey more specific meaning to the science-based context of our study, are non-judgemental, and describe more of a continuum from unitary discipline focus (focused) to multiple foci (diversified). More importantly, it is possible for both generalists and specialists to be either focused or diversified and so the comparison is not direct but rather a simplification of these social categorizations.

### 2.2. Focused and diversified profiles as outcomes of social categorization

The literature on entrepreneurial teams often distinguishes between two types of individual human capital that reflect different kinds of expertise; namely, specific human capital (special interest knowledge and skills) versus varied human capital (occupational variety and experience) (e.g. Astebro & Thompson, 2011; Corbett, 2007; Dimov & Shepherd, 2005; Marvel, 2013; Ucbasaran et al., 2008; Zarutskie, 2010). Specific human capital denotes a *focused profile*, which reflects the ability to integrate deep knowledge of a discipline with the knowledge of how it interacts with cognate disciplines (Iansiti, 1993). As such, people with focused profiles are *experts* in a specific domain but understand how their expertise can potentially be translated and applied outside of their core domain. The depth of one's own specialist knowledge base is complemented by—and interacts with—diverse general knowledge bases, often obtained via networks of external relations (Grandi & Grimaldi, 2005; Leonard-Barton, 1995). In entrepreneurial teams, members with focused profiles tend to direct their effort into applying expert skills and practicing craftsmanship in a domain they specialize in (Warnick et al., 2018).

Occupationally varied human capital denotes a *diversified profile*, which refers to individuals with a background in two professional areas with *relative expertise* in each (Leonard-Barton, 1995). This enables the individual to develop cognitive resources necessary to integrate insights from multiple perspectives, create synergies between distinct knowledge domains, and balance trade-off decisions. Such individuals are often described as "jacks-of-all-trades" (Lazear, 2004, 2005) with a balanced skill set (Stuetzer et al., 2013), willing and capable of taking on a variety of roles simultaneously and crossing disciplinary boundaries as they found and develop their ventures (Mathias & Williams, 2017). Individuals with diversified profiles, being skilled in multiple professional areas are able to combine different resources and ideas to enable success of the venture (Lazear, 2005).[2]

R&D teams are often referred to as knowledge-producing structures, in which individuals with cross-functional skills are brought together to produce knowledge collectively. Hence, R&D-focused entrepreneurial ventures have a strong rationale to create team structures that rely on profile differentiation (Visintin & Pittino, 2014). Empirical evidence suggests that scientists with both focused and diversified profiles are likely to be strong in terms of inventiveness (Zwick et al., 2017). Furthermore, the literature indicates that diversified profiles are correlated with an entrepreneurial personality profile (Stuetzer et al., 2013). According to within-work role identity theory, *"depending on the role identity assumed, entrepreneurs attend to different opportunity features and make different decisions with regard to opportunity consideration and selection"* (Mathias & Williams, 2017, p. 892). Hence, the role that an entrepreneur (i.e. an individual with a diversified profile) assumes within a team can define the course of the venture's development and be pivotal in the way the venture creates future value. Despite the apparent logic of these theoretical premises, little empirical evidence exists linking profile differentiation to entrepreneurial team roles in explaining venture performance.

### 2.3. Conceptual framework

We focus on two key roles that are typical for R&D-focused entrepreneurial teams: (i) a principal scientist, or lead researcher and (ii) a manager, or commercial lead. To understand how a combination of individual human capital and career development pathways is exhibited in the way principal scientists and managers carry out their tasks within the entrepreneurial team, we distinguish between focused and diversified profiles. Such conceptual delineation results in two complementary within-team profile-to-role configurations. One possible configuration is when a principal scientist has a diversified profile and a manager has a focused profile, whereas another configuration is when a principal scientist has a focused profile, and a manager has a diversified profile. We expect that focused and diversified profiles aligned to specific roles enable knowledge complementarity within teams, leading to positive venture outcomes. We further empirically test whether these within-team configurations might result in differential new venture outcomes.[3]

## 3. Methodology

### 3.1. Research setting, sample, and data collection

To examine the effects of focused and diversified profiles on venture performance, we constructed a dataset of small firms that received funding under the SBIR program in the U.S., which can be found at: https://www.sbir.gov/sbirsearch/award/all. The primary aim of the program is to fuel the growth of the U.S. economy by encouraging small businesses to explore their entrepreneurial and technological potential, stimulating commercialization of the technology, product, or service spurring from R&D and innovation activities. To win an award under the initiative, small firms are required to demonstrate the scientific and commercial potential of participating projects. For these reasons, the SBIR initiative represents a suitable context for testing which configurations of skills within entrepreneurial teams lead to R&D and commercial outcomes.

We made a series of methodological decisions to ensure a robust sampling frame. First, to reduce the heterogeneity among projects in the sample frame, the U.S. National Institutes of Health (NIH) was selected as the most relevant setting due to its propensity to fund high-technology projects with a strong incentive to commercialize. As indicated by the NIH, "Many companies leverage NIH funding to attract the partners and investors needed to take an innovation to market. We focus on a variety of high-impact technologies ranging from research tools, diagnostics, digital health, drugs, medical devices, and others. The NIH SBIR […] programs can provide the seed funding […] need[ed] to bring […] scientific innovations from bench to bedside."[4]

Then, the sample was further limited to the projects funded by the National Cancer Institute. Oncology research has evolved separately yet in parallel with generic drug development technological platforms, and forms the basis for the market of anticancer drugs and treatments (Sosa, 2009). The anticancer market is science-intensive with firm profitability normatively associated to research competence and product quality (Lu & Comanor, 1998). This latter characteristic aligns with our focus on the connection between skills and R&D production and commercialization. The list of participating firms funded under the SBIR program was retrieved from the SBIR database and cross-checked against the RePORTER database of the NIH (available at: https://reporter.nih.gov). We randomly generated an initial sample of 383 projects from the period 2006–2011.[5]

Data were collected on individual-level and firm-level characteristics. Individual-level characteristics capture two important units of

[2] We do not explicitly address the wider institutional environment in this study because, as indicated by Dvoulety et al. (2021), the rules of the game are different in early-stage ventures where public funds are used as compared to other contexts such as venture capital investment. However, for the interested reader, we suggest this adjacent literature and recommend Fini et al. (2017), Fini et al. (2019), Wright and Phan (2018), and Urbano et al. (2020).

[3] The direct effects of individual-level focused and diversified profiles are not explicitly discussed. Rather, they are taken as baseline relationships and results are shown in Table 3.

[4] This is described by the NIH where further details can be retrieved from: https://seed.nih.gov/small-business-funding/small-business-program-basics/understanding-sbir-sttr (Accessed on 2 November 2022).

[5] 383 observations allow to capture the characteristics of the population of 100,000 cases at the 95% confidence level.

analysis—manager and scientist. The manager is defined as the individual assigned in the database as the "business contact", whereas the scientist is a "principal investigator" responsible for the execution of the project. SBIR and NIH databases were used to generate a list of individuals' names. LinkedIn was employed to generate data on their human capital and supplemented by biographies published on companies' websites and several additional secondary data sources (available at: https://www.linkedin.com). Elsevier's Scopus database of peer-reviewed literature was used to collect data on their academic performance (available at: https://www.scopus.com). These variables are further described in Table 1.

Firm-level data gathering was focused on firms' attributes such as sales, patenting activity, size, age, and business activity. SBIR participants are small private firms, which means that obtaining data on firm size and financial performance is a major challenge because in the U.S. such firms are not legally required to report their financial performance. Hoover's Online database, which is devoted to small and private companies, was used to capture the latest data on sales and number of employees (available at: https://www.dnb.com/products/marketing-sales/dnb-hoovers.html), as well as industry codes and classifications and supplemented by Bloomberg Business Week. PatBase was used as the primary source to collect data on firms' patenting activity (available at: https://www.patbase.com), complemented by the Espacenet database (available at: https://worldwide.espacenet.com) of the European Patent Office.

Following data collection and initial examination of the data, many cases were identified for deletion due to an excessive number of missing values, and several cases were deleted as significant outliers. Furthermore, we manually checked the data to ensure that the "business contact" referred to individuals in managerial rather than administrative positions. These steps resulted in a working sample of 153 observations.

### 3.2. Dependent variables

#### 3.2.1. Commercial performance

Business-related performance outcomes are characterized as the effectiveness of using available resources to commercialize a product in the market.[6] We chose to capture commercial performance in terms of labor productivity and operationalize this as sales per employee. In choosing between absolute versus relative measure of commercial performance, we were driven by two primary considerations. First, given that our research focus is on individual scientists and managers as the primary units of analysis, normalizing sales by employees (and hence focusing on labor productivity) enabled us to relate individual contributions to firm performance. Furthermore, for consistency, both commercial performance and R&D performance (described below) were chosen as measures of productivity, one capturing labor productivity and another research productivity. The rationale underlying choosing these measures of productivity was that small entrepreneurial firms, such as those analyzed in our sample, operate with extremely limited resources so direct productivity reflects the efficiency with which they

**Table 1**
Summary of variables.

| Variable | Measurement | Data Source |
|---|---|---|
| R&D performance | SFE Equation:<br>Output: patent applications following the commencement of the project by firm $i$ in years $t$+1, $t$+2, $t$+3; count, log-transformed<br>Input 1: citation-weighted patent stock by firm $i$ prior to year $t$; weighted count, log-transformed<br>Input 2: patent classes firm acquired by firm $i$ prior to year $t$; count, log-transformed<br>Input 3: R&D funds received from SBIR by firm $i$ in years $t$, $t$-1, $t$-2; $ million, log-transformed | Patbase & Espacenet; SBIR data |
| Commercial performance | Sales by employee of firm $i$: revenue in $t_{2013}$ ($ million) divided by the number of employees in $t_{2013}$; log-transformed | Hoover's Online, Bloomberg Business Week |
| CEO | Whether or not the person is a CEO, dummy | LinkedIn |
| Founder | Whether or not the person is a founder, dummy | LinkedIn |
| PhD | Whether or not the person has a doctorate degree, dummy | LinkedIn |
| MBA | Whether or not the person has an MBA degree, dummy | LinkedIn |
| STEM degree | Whether or not the person has a STEM degree, dummy | LinkedIn |
| Professor | Whether or not the person is a professor, dummy | LinkedIn |
| Experience | Average of industry experience, entrepreneurial experience, commercial experience<br>Industry experience = experience in biotech and life sciences prior to year $t$<br>Entrepreneurial experience = experience as an entrepreneur in any sector prior to year $t$<br>Commercial experience = experience in managerial or other commercial positions in any sector prior to year $t$ | LinkedIn |
| Education quality | Average of elite institution score, faculty quality, research output<br>Elite institution score = top worldwide universities score (or zero if not in the ranking) in year $t$<br>Quality of faculty = global score that refers to the number of highly cited researchers in 21 broad subject categories in year $t$<br>Research output = global score that refers to the weighted number of articles indexed in Science and Social Science Citation Index in year $t$ | ARWU[a] |
| Academic quality | Average of academic competence, academic value, academic impact<br>Academic competence = total number of published documents, including peer-reviewed journal articles, conference articles, books, etc. prior to year $t$; count, log-transformed<br>Academic value = number of citations prior to year $t$; count, log-transformed<br>Academic impact = h-index (at project start date) in year $t$; score, log-transformed | Elsevier's Scopus |
| Firm age | Number of years from founding to project start in year $t$; count, log-transformed | Company website; Bloomberg Business Week |

(continued on next page)

[6] There is a wide range of different performance measures employed in the studies on new ventures and there is no unitary theory on how human capital relates to different criteria of entrepreneurial performance (Gerschewski & Xiao, 2015; Unger et al., 2011). Essentially, the choice between different measures is a trade-off between capturing, for example, short-term versus long-term objectives, unidimensional versus multidimensional performance, subjective versus objective performance, financial versus operational versus effectiveness measures, each having advantages and limitations. That is, using profitability may represent a time lag that is too short in the evaluation of how human capital affects new venture performance, whereas using growth may be contingent upon individual entrepreneur's motivation to expand the enterprise. For a detailed discussion of issues surrounding measurement of new venture performance, please refer to Gerschewski and Xiao (2015) and Unger et al. (2011).

**Table 1** (*continued*)

| Variable | Measurement | Data Source |
|---|---|---|
| Patenting experience | Number of years since the first filed patent to project start in year *t*; count, log-transformed | Patbase & Espacenet |
| Industry volatility | Standard deviation from average annual equal-weighted returns of the Fama and French (1997) for 49 industries for a 5-year rolling window (t-1, …, t-5), lagged by 1 year.[b] | Ken French Data Library |
| Same person team | Whether or not the same person is manager and scientist, dummy | |
| Team experience difference | Absolute difference in experience between manager and scientist | |
| Team education quality difference | Absolute difference in education quality between manager and scientist | |
| Team academic quality difference | Absolute difference in academic quality between manager and scientist | |
| Year dummies | Year *t* of project start (2006–2011) | SBIR data |

Notes: R&D = Research and Development, SFE = Stochastic Frontier Estimation, SBIR = Small Business Innovation Research, CEO = Chief Executive Officer, PhD = Doctor of Philosophy/Professional Doctorate, MBA = Master of Business Administration, STEM = Science, Technology, Engineering or Mathematics, ARWU = Academic Ranking of World Universities.

[a] The league table included the scores of the best 500 institutions ranked on several categories of academic and research performance, each with a maximum score of 100.

[b] The industry volatility control variable was constructed following the procedure described by Peters and Wagner (2014). First, industry classifications were matched with the Standard Industrial Classification (SIC) code list reported in the EDGAR database of the U.S. Securities and Exchange Commission (SEC). Next, four-digit SIC codes were grouped according to the Fama-French classifications (Fama & French, 1997) of 49 industries. Finally, a list of market returns on a portfolio of 49 industries was retrieved from the Kenneth R. French Data Library. Industry stock return volatility was computed using 5-year windows of the average equal-weighted annual returns of the Fama-French 49 industries. The majority of firms in our sample fall under one the following industries and this variation is accounted for in our models: Commercial/Non-commercial Physical and Biological Research, Healthcare, Measuring and Control Equipment, Medical Equipment, Pharmaceutical Products.

use available resources (e.g., employees, knowledge) to achieve desired outcomes (e.g., sales, patent applications). Such is the performance chain-of-effects in small ventures as these, where the lagged effect of other commercial outcomes, for example, profitability, is too indirect a measure (Delmar et al., 2003; Dvoulety et al., 2021).

#### 3.2.2. R&D performance

Innovation-related performance outcome is captured in terms of research productivity, and reflects firms' efficiency of converting inputs into outputs (Fried et al., 2008). Following the logic of the operationalization proposed by Dutta et al. (1999, 2005), the measure of R&D performance was expressed by the frontier function. This measure was estimated using stochastic frontier analysis and expressed by the following Cobb-Douglas logarithmic specification (Coelli et al., 2005), with estimation results reported in the Appendix:

$$\begin{aligned} log\left(Patent\ applications_{t+1,t+2,t+3}\right) = \beta_0 + \beta_1 \times log(&Citation \\ &- weighted\ patent\ stock) + \beta_2 \\ &\times log(Patent\ classes) + \beta_3 \\ &\times log\left(R\&D\ funds_{t,t-1,t-2}\right) \times exp\ (V_{it}) \\ &\times exp\ (-U_{it}) \end{aligned}$$

Patentable knowledge is a manifestation of inventive activity and serves three primary strategic purposes: protection of intellectual property, commercialization of new know-how in the form of product innovation or licensing, and an indication of R&D performance (Blind et al., 2006). Here, inventive activity was operationalized as a firm's patenting performance, measured by the count of filed patent applications in the window of three years following the commencement of an R&D project (Andries & Faems, 2013). To account for differences in the value of patented knowledge, patents were adjusted by their quality (e.g., Levitas & McFadyen, 2009). The measure of citation-weighted patent stock was adopted from Dutta et al. (1999).[7] Global patenting offices use an international patent classifications (IPC) system to allocate patents to appropriate technological classes. The count of patent classifications (i.e. the stock of firm's IPCs) was used as a proxy to measure the knowledge breadth contained in a patent, which indicates its future potential value.

### 3.3. Independent variables

#### 3.3.1. Human capital

We collected data on several key human capital characteristics. First, we captured managers' and principal scientists' additional functions within the team, i.e., whether they were a Chief Executive Officer (CEO), a founder, or a professor[8] when a project started. We also recorded whether they held a Doctor of Philosophy/Professional Doctorate (PhD), a Master of Business Administration (MBA) degree, or a Science, Technology, Engineering or Mathematics (STEM) degree.[9]

In addition, we gathered information on the types of experience, education, and performance as an academic, which resulted in nine indicators from which our variables were derived (these are illustrated in Table 1). The measure of "manager's/principal scientist's experience" captures the breadth of professional experiences and is an average of industry experience, entrepreneurial experience, and commercial experience, where industry experience refers to experience in biotech and life sciences, entrepreneurial experience refers to experience as an entrepreneur in any sector, and commercial experience refers to experience in managerial or other commercial positions in any sector. Education quality refers to the subject's last attended academic institution. Indicators of institution quality were determined by the Academic Ranking of World Universities (ARWU) published by the Shanghai Ranking Consultancy. The measure of education quality is an average of institutions' scores related to their elite status, quality of faculty, and overall research output. Finally, academic quality captures excellence and productivity related to academic research of a manager and principal scientist. Academic quality is measured by the means of manager's and scientist's competence (number of publications), value (number of citations), and impact (h-index).

#### 3.3.2. Focused and diversified profiles

Indicators of focused profiles may include a narrow set of professional interests, experiences, and networks (Grandi & Grimaldi, 2005; Visintin & Pittino, 2014). Diversified profiles, on the other hand, may be evident by on-the-job experience in multiple functions (Astebro & Thompson, 2011; Stuetzer et al., 2013). We operationalize a focused profile as an interaction of two human capital characteristics, i.e., academic quality and education quality. Academic quality represents the depth of scientific expertise, whereas education quality reflects the connections to supplementary knowledge bases via external networks

[7] First, the average number of citations received by all previously filed patents by all firms in the sample was calculated. Then, the weight was determined as a ratio of firm *i* citations to the sample average. To arrive at the value of citation-weighted patents, this weight was then assigned as a multiplier to the total number of patents filed by firm *i*.

[8] These categories are not mutually exclusive. In fact, the nature of the studied teams (i.e., small and/or young) makes it possible for a team member to fulfil multiple functions concurrently.

[9] Later, these variables related to scientists were omitted from the analysis as there was no variation; i.e., over 95% of scientists in the sample had been awarded a PhD and a STEM degree, but not an MBA.

**Table 2**
Descriptive statistics and correlations (N = 153).

| | Variable | Mean | SD | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | R&D performance | 0.16 | 0.25 | 1.00 | | | | | | | | | | | | |
| (2) | Commercial performance | 0.24 | 0.13 | 0.28 | 1.00 | | | | | | | | | | | |
| (3) | Manager CEO | 0.62 | 0.49 | −0.19 | −0.20 | 1.00 | | | | | | | | | | |
| (4) | Scientist CEO | 0.46 | 0.50 | 0.07 | −0.01 | 0.20 | 1.00 | | | | | | | | | |
| (5) | Manager Founder | 0.64 | 0.48 | −0.04 | −0.08 | 0.57 | 0.23 | 1.00 | | | | | | | | |
| (6) | Scientist Founder | 0.55 | 0.50 | 0.16 | 0.03 | 0.22 | 0.66 | 0.41 | 1.00 | | | | | | | |
| (7) | Manager PhD | 0.67 | 0.47 | −0.04 | −0.15 | 0.30 | 0.23 | 0.36 | 0.22 | 1.00 | | | | | | |
| (8) | Manager MBA | 0.19 | 0.39 | 0.13 | 0.07 | −0.12 | −0.17 | −0.21 | −0.15 | −0.49 | 1.00 | | | | | |
| (9) | Manager STEM | 0.80 | 0.40 | −0.07 | −0.17 | 0.46 | 0.04 | 0.42 | 0.12 | 0.60 | −0.26 | 1.00 | | | | |
| (10) | Manager Professor | 0.40 | 0.45 | −0.15 | −0.05 | 0.36 | 0.12 | 0.37 | 0.15 | 0.45 | −0.28 | 0.25 | 1.00 | | | |
| (11) | Scientist Professor | 0.34 | 0.47 | 0.00 | 0.01 | 0.14 | 0.16 | 0.14 | 0.28 | 0.04 | −0.04 | −0.01 | 0.46 | 1.00 | | |
| (12) | Manager experience | 12.33 | 7.87 | −0.20 | 0.00 | 0.39 | 0.12 | 0.24 | 0.12 | 0.11 | −0.13 | 0.12 | 0.26 | 0.14 | 1.00 | |
| (13) | Scientist experience | 10.52 | 7.06 | 0.07 | 0.05 | 0.16 | 0.45 | 0.17 | 0.44 | 0.10 | −0.13 | −0.04 | 0.10 | 0.17 | 0.53 | 1.00 |
| (14) | Manager education quality | 35.05 | 26.03 | 0.10 | −0.02 | 0.15 | 0.00 | 0.13 | 0.11 | 0.05 | −0.06 | 0.00 | 0.10 | 0.11 | 0.04 | 0.03 |
| (15) | Scientist education quality | 34.28 | 22.92 | 0.16 | −0.04 | −0.03 | 0.21 | −0.01 | 0.13 | 0.03 | −0.02 | −0.18 | 0.07 | 0.12 | −0.09 | 0.06 |
| (16) | Manager academic quality | 12.42 | 5.91 | 0.01 | −0.03 | 0.29 | 0.19 | 0.41 | 0.17 | 0.77 | −0.48 | 0.58 | 0.57 | 0.10 | 0.20 | 0.05 |
| (17) | Scientist academic quality | 32.53 | 2.66 | 0.23 | 0.09 | 0.01 | 0.09 | −0.02 | 0.23 | 0.15 | −0.06 | 0.07 | 0.21 | 0.40 | 0.10 | 0.19 |
| (18) | Firm age | 5.64 | 1.16 | −0.18 | 0.27 | −0.04 | 0.01 | 0.01 | −0.06 | −0.07 | −0.16 | −0.11 | 0.05 | 0.08 | 0.43 | 0.38 |
| (19) | Patenting experience | 2.04 | 1.82 | −0.11 | 0.25 | −0.05 | −0.08 | −0.04 | −0.05 | −0.09 | −0.07 | −0.08 | 0.00 | 0.05 | 0.27 | 0.14 |
| (20) | Industry volatility | 18.11 | 6.11 | 0.08 | 0.00 | −0.08 | −0.11 | −0.16 | −0.09 | 0.05 | −0.04 | 0.07 | −0.14 | −0.16 | −0.20 | −0.06 |
| (21) | Same person team | 0.40 | 0.49 | −0.13 | −0.12 | 0.26 | 0.51 | 0.30 | 0.43 | 0.44 | −0.29 | 0.34 | 0.20 | 0.11 | −0.01 | 0.17 |
| (22) | Team experience difference | 4.30 | 6.14 | 0.12 | −0.02 | −0.06 | −0.29 | −0.05 | −0.26 | −0.20 | 0.11 | −0.05 | 0.00 | 0.00 | 0.33 | −0.07 |
| (23) | Team education quality difference | 14.51 | 19.48 | 0.10 | 0.09 | −0.19 | −0.27 | −0.11 | −0.18 | −0.33 | 0.20 | −0.26 | −0.14 | 0.01 | −0.02 | 0.01 |
| (24) | Team academic quality difference | 3.09 | 4.31 | 0.06 | 0.14 | −0.31 | −0.32 | −0.35 | −0.18 | −0.65 | 0.39 | −0.50 | −0.28 | 0.02 | −0.06 | −0.10 |

| | Variable | Mean | SD | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (14) | Manager education quality | 35.05 | 26.03 | 1.00 | | | | | | | | | | |
| (15) | Scientist education quality | 34.28 | 22.92 | 0.51 | 1.00 | | | | | | | | | |
| (16) | Manager academic quality | 12.42 | 5.91 | 0.08 | 0.02 | 1.00 | | | | | | | | |
| (17) | Scientist academic quality | 32.53 | 2.66 | 0.21 | 0.00 | 0.29 | 1.00 | | | | | | | |
| (18) | Firm age | 5.64 | 1.16 | −0.02 | −0.08 | −0.03 | 0.02 | 1.00 | | | | | | |
| (19) | Patenting experience | 2.04 | 1.82 | −0.06 | −0.08 | −0.06 | 0.05 | 0.44 | 1.00 | | | | | |
| (20) | Industry volatility | 18.11 | 6.11 | −0.03 | 0.00 | 0.05 | −0.02 | 0.03 | 0.01 | 1.00 | | | | |
| (21) | Same person team | 0.40 | 0.49 | 0.00 | 0.03 | 0.38 | −0.04 | −0.07 | −0.11 | −0.02 | 1.00 | | | |
| (22) | Team experience difference | 4.30 | 6.14 | −0.08 | −0.01 | −0.12 | −0.02 | 0.12 | −0.06 | −0.10 | −0.51 | 1.00 | | |
| (23) | Team education quality difference | 14.51 | 19.48 | 0.14 | 0.02 | −0.26 | 0.04 | 0.10 | −0.01 | 0.08 | −0.59 | 0.34 | 1.00 | |
| (24) | Team academic quality difference | 3.09 | 4.31 | 0.07 | 0.00 | −0.62 | 0.16 | 0.01 | 0.03 | −0.08 | −0.66 | 0.35 | 0.48 | 1.00 |

Notes: Correlations above |0.16| are significant at $p < 0.05$, above |0.21| are significant at $p < 0.01$, above |0.26| are significant at $p < 0.001$ (2-tailed).
R&D = Research and Development, CEO = Chief Executive Officer, PhD = Doctor of Philosophy/Professional Doctorate, MBA = Master of Business Administration, STEM = Science, Technology, Engineering or Mathematics.

and relations. The affiliation with the last attended academic institution grants its alumni access to prestigious social capital in a broad range of disciplines and other resources available through network ties. This is particularly evident in the case of elite universities where connections in alumni networks are mostly strong. Diversified profiles refer to combinations of two occupational areas. As we could observe two types of diversified profiles in our sample, they were operationalized as an interaction of science and business (Professor x CEO) and science and entrepreneurship (Professor x Founder).

### 3.3.3. *Control variables*

We further controlled for firm and team characteristics that may influence R&D and commercial performance of science-driven small firms. In some instances, the same person was listed under the project description as both a manager and a scientist. To control for such cases, we created a dummy variable representing the same person team. We also controlled for team-level potential complementary or overlapping skills by calculating the absolute difference in education quality, academic quality, and experience of the two team members. Industry stock return volatility was used as a proxy for industry risk, which is likely to affect commercial performance. This variable was operationalized as the absolute deviation of the average annual equal-weighted returns from the average in the preceding 5-year rolling window and lagged by one fiscal year of the reported sales date to reduce potential simultaneity concerns. We also included patenting experience, firm age, and year dummies as additional controls. All measures are summarized in Table 1 and the correlation matrix is depicted in Table 2.

## 4. Results

### 4.1. *Baseline results*

Table 3 shows the results of the baseline models, which include both the control and human capital variables and the interaction effects of

**Table 3**
Results of regression analyses for R&D and commercial performance: baseline effects of scientist's and manager's human capital and individual effects of scientist's and manager's focused and diversified profiles.

| Dependent variable | Scientist | | Manager | |
|---|---|---|---|---|
| | R&D performance | Commercial performance | R&D performance | Commercial performance |
| *Direct effects* | | | | |
| CEO | 0.04 (0.23) | 0.05 (0.24) | −0.26 (0.24) | −0.26 (0.24) |
| Founder | 0.36 (0.23) | 0.25 (0.24) | 0.21 (0.21) | 0.14 (0.22) |
| PhD | | | −0.04 (0.31) | −0.35 (0.31) |
| MBA | | | 0.41 (0.26) | 0.32 (0.25) |
| STEM degree | | | −0.16 (0.31) | −0.20 (0.34) |
| Professor | −0.33* (0.19) | −0.16 (0.20) | −0.43* (0.23) | −0.12 (0.23) |
| Experience | 0.10 (0.09) | −0.10 (0.10) | −0.13 (0.11) | −0.08 (0.11) |
| Education quality | 0.07 (0.08) | −0.02 (0.09) | 0.11 (0.08) | 0.00 (0.09) |
| Academic quality | 0.23** (0.09) | 0.07 (0.10) | 0.31** (0.15) | 0.38** (0.16) |
| *Controls* | | | | |
| Firm age | −0.19* (0.10) | 0.29*** (0.11) | −0.09 (0.10) | 0.28*** (0.10) |
| Patenting experience | −0.04 (0.09) | 0.14 (0.10) | 0.00 (0.10) | 0.16 (0.10) |
| Industry volatility | | −0.02 (0.12) | | −0.03 (0.12) |
| Same person team | −0.64** (0.28) | −0.27 (0.29) | −0.31 (0.28) | −0.14 (0.27) |
| Team experience difference | 0.09 (0.10) | −0.11 (0.10) | 0.15 (0.12) | −0.09 (0.12) |
| Team education quality difference | 0.00 (0.10) | 0.03 (0.10) | −0.03 (0.10) | −0.02 (0.10) |
| Team academic quality difference | −0.16 (0.11) | 0.07 (0.11) | −0.07 (0.13) | 0.12 (0.14) |
| Year dummies | Incl. | Incl. | Incl. | Incl. |
| Constant | 0.70*** (0.24) | 0.20 (0.27) | 0.90*** (0.35) | 0.67* (0.36) |
| $R^2$ | 0.27 | 0.16 | 0.25 | 0.22 |
| *Individual effects of profile types* | | | | |
| Focused | 0.21** (0.09) | 0.11 (0.10) | 0.18** (0.08) | 0.15* (0.08) |
| Diversified (Professor x Founder) | 0.44 (0.37) | 0.23 (0.40) | −0.26 (0.66) | −0.78 (0.67) |
| Diversified (Professor x CEO) | 0.78** (0.32) | 0.44 (0.36) | 0.25 (0.60) | −0.05 (0.58) |

Notes: Baseline predictors are listed above the line; individual effects of profile types below the line were added to baseline predictors one-by-one; all regression coefficients are standardized; standard errors are in parentheses. R&D = Research and Development, CEO = Chief Executive Officer, PhD = Doctor of Philosophy/Professional Doctorate, MBA = Master of Business Administration, STEM = Science, Technology, Engineering or Mathematics.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; N = 153.

human capital variables that comprise focused and diversified profiles.[10] Focused profiles of scientists and managers have a direct positive effect on R&D performance (β = 0.21, $p < 0.05$ and β = 0.18, $p < 0.05$, respectively). Managers' focused profiles also have a weak positive direct effect on commercial performance (β = 0.15, $p < 0.1$) but not scientists' focused profiles. These results show general support for the baseline expectation that individuals with focused profiles have a positive influence on team performance. However, the results of the baseline models show little evidence of the expected positive effect of diversified profiles. No combinations of scientists' or managers' diversified profiles were found to affect either R&D performance or commercial performance.

### 4.2. Results of within-team profile-to-role configurations

The results shown in Table 4 refer to the model that depicts the conceptual configuration with a manager's focused profile and a scientist's diversified profile. Scientists that are founders (β = 0.60, $p < 0.05$) have a positive impact on R&D performance. In contrast, managers' experience has a negative impact on R&D performance (β = −0.27, $p < 0.05$). Managers' academic quality has a stronger positive influence on commercial performance (β = 0.40, $p < 0.01$) than on R&D performance (β = 0.24, $p < 0.1$). Also, the dummy variable controlling for teams with the same member handling both a manager's and scientist's roles has a negative impact on R&D (β = −0.68, $p < 0.05$), suggesting that NPD is a team rather than an individual endeavor. Finally, firm age is a strong predictor of commercial performance (β = 0.33, $p < 0.01$).

The lower part of Table 4 shows evidence that configurations of a manager's focused profile and a scientist's diversified profile combined as Professor x Founder (β = 0.34, $p < 0.05$) and Professor x CEO (β = 0.50, $p < 0.01$) have a strong positive effect on R&D performance. The latter combination has a positive but weak effect on commercial performance (β = 0.31, $p < 0.1$).

Table 5 shows results of the model that refers to the configuration comprising scientists' focused profile and managers' diversified profile. Under this team configuration, managers holding CEO (β = −0.50, $p < 0.05$) and professorship positions (β = −0.34, $p < 0.1$) negatively affect R&D performance. On the other hand, scientist's experience (β = 0.19, $p < 0.05$) and academic quality (β = 0.27, $p < 0.01$) are significant contributors to R&D performance. The results of the model for the second dependent variable show that managers holding a CEO position (β = −0.41, $p < 0.1$) weakly influence commercial performance. Firm age appears to be negatively associated with R&D performance (β = −0.23, $p < 0.05$) and positively with commercial performance (β = 0.25, $p < 0.05$). Finally, differences in the academic quality of team members (β = −0.28, $p < 0.05$) and same person teams (β = −0.28, $p < 0.05$) are negatively associated with R&D performance.

The lower part of Table 5 further shows that no combinations of a scientist's focused profile and managers' diversified profile influence R&D performance. However, the latter configuration has a significant effect on commercial performance when scientists' focused profiles are combined with managers' diversified profiles: Professor x Founder (β = 0.34, $p < 0.1$) and Professor x CEO (β = 0.40, $p < 0.05$).

## 5. Discussion

### 5.1. Theoretical and practical implications

In this study, we sought to understand whether the presence of differentiated profiles within key roles in entrepreneurial teams can have effects on different dimensions of new venture performance. In developing our conceptual framework, we drew an analogy to prior studies (e.g. Berg, 2016; Ter Wal et al., 2020), where the distinction is made between the social categorizations of innovator and business roles in the way they apply their knowledge and experience to the innovation process in organizations. We tested the effects of two complementary within-team profile-to-role configurations on R&D and commercial performance. Based on our study of the roles of focused and diversified profiles in scientist-manager entrepreneurial R&D-focused teams, we make three observations.

[10] We calculated variance inflation factors (VIF) for all models to establish whether multicollinearity might be present. The statistics were within acceptable limits, with the mean VIF below 3.00, indicating that multicollinearity was not a problem. Regression equations were modeled using standardized data to minimize heterogeneity across different units of measurement that varied across the variables in the models.

**Table 4**
Results of regression analyses for R&D and commercial performance: effects of team configuration with scientist's diversified profile and manager's focused profile.

| Dependent variable | R&D performance | Commercial performance |
|---|---|---|
| *Direct effects* | | |
| Scientist CEO | 0.19 (0.22) | −0.05 (0.23) |
| Scientist Founder | 0.60**(0.24) | 0.31 (0.23) |
| Scientist Professor | −0.18 (0.18) | −0.17 (0.18) |
| Manager PhD | −0.22 (0.30) | −0.40 (0.31) |
| Manager MBA | 0.44* (0.24) | 0.33 (0.25) |
| Manager STEM degree | −0.10 (0.27) | −0.28 (0.31) |
| Manager experience | −0.27*** (0.09) | −0.16 (0.10) |
| Manager education quality | 0.09 (0.08) | −0.02 (0.08) |
| Manager academic quality | 0.24* (0.13) | 0.40*** (0.14) |
| *Controls* | | |
| Firm age | −0.03 (0.10) | 0.33*** (0.10) |
| Patenting experience | 0.02 (0.09) | 0.17 (0.10) |
| Industry volatility | | −0.04 (0.12) |
| Same person team | −0.68** (0.28) | −0.23 (0.29) |
| Team experience difference | 0.21* (0.11) | −0.06 (0.12) |
| Team education quality difference | −0.05 (0.10) | −0.02 (0.10) |
| Team academic quality difference | −0.16 (0.13) | 0.10 (0.14) |
| Year dummies | Incl. | Incl. |
| Constant | 0.61* (0.34) | 0.62* (0.36) |
| $R^2$ | 0.30 | 0.22 |
| *Interaction effects of profile types* | | |
| Diversified Scientist (Professor x Founder) x Focused Manager | 0.34** (0.14) | 0.21 (0.14) |
| Diversified Scientist (Professor x CEO) x Focused Manager | 0.50*** (0.16) | 0.31* (0.17) |

Notes: Team configuration effects are listed above the line; interaction effects of profile types below the line were added to baseline predictors one-by-one; all regression coefficients are standardized; standard errors are in parentheses. R&D = Research and Development, CEO = Chief Executive Officer, PhD = Doctor of Philosophy/Professional Doctorate, MBA = Master of Business Administration, STEM = Science, Technology, Engineering or Mathematics.
***p < 0.01; **p < 0.05; *p < 0.1; N = 153.

**Table 5**
Results of regression analyses for R&D and commercial performance: effects of team configuration with scientist's focused profile and manager's diversified profile.

| Dependent variable | R&D performance | Commercial performance |
|---|---|---|
| *Direct effects* | | |
| Scientist experience | 0.19** (0.09) | −0.02 (0.09) |
| Scientist education quality | 0.10 (0.08) | −0.02 (0.09) |
| Scientist academic quality | 0.27*** (0.09) | 0.09 (0.10) |
| Manager CEO | −0.50** (0.21) | −0.41* (0.23) |
| Manager Founder | 0.27 (0.20) | 0.21 (0.22) |
| Manager PhD | −0.11 (0.30) | −0.12 (0.33) |
| Manager MBA | 0.31 (0.24) | 0.22 (0.26) |
| Manager STEM degree | 0.12 (0.34) | −0.06 (0.40) |
| Manager Professor | −0.34* (0.20) | 0.08 (0.23) |
| *Controls* | | |
| Firm age | −0.23** (0.10) | 0.25** (0.11) |
| Patenting experience | −0.04 (0.09) | 0.13 (0.10) |
| Industry volatility | | 0.00 (0.12) |
| Same person team | −0.52** (0.26) | −0.18 (0.28) |
| Team experience difference | 0.10 (0.10) | −0.11 (0.11) |
| Team education quality difference | −0.03 (0.10) | 0.00 (0.11) |
| Team academic quality difference | −0.28** (0.13) | −0.02 (0.14) |
| Year dummies | Incl. | Incl. |
| Constant | 0.85*** (0.31) | 0.39 (0.33) |
| $R^2$ | 0.32 | 0.19 |
| *Interaction effects of profile types* | | |
| Focused Scientist x Diversified Manager (Professor x Founder) | 0.25 (0.16) | 0.34* (0.18) |
| Focused Scientist x Diversified Manager (Professor x CEO) | 0.25 (0.17) | 0.40** (0.18) |

Notes: Team configuration effects are listed above the line; interaction effects of profile types below the line were added to baseline predictors one-by-one; all regression coefficients are standardized; standard errors are in parentheses. R&D = Research and Development, CEO = Chief Executive Officer, PhD = Doctor of Philosophy/Professional Doctorate, MBA = Master of Business Administration, STEM = Science, Technology, Engineering or Mathematics.
***p < 0.01; **p < 0.05; *p < 0.1; N = 153.

First, individuals with focused profiles have a positive influence on venture performance, but the expected direct positive effect of diversified profiles is limited. Second, combining a scientist's focused profile and a manager's diversified profile (i.e., Professor x Founder and Professor x CEO) leads to favorable improvements in commercial performance but not R&D performance. Third, a combination of a scientist's diversified profile (i.e., Professor x Founder and Professor x CEO) and a manager's focused profile strongly influence R&D performance in a positive manner, but this impact is weak for commercial performance. These findings add to the literature on R&D team composition (e.g. Garcia Martinez et al., 2017; Iseke et al., 2015), entrepreneurial team human capital (e.g. Belso-Martinez et al., 2013; Le et al., 2013), and entrepreneurial founding teams (e.g. Patzelt et al., 2009; Zolin et al., 2011), and suggest several contributions and implications.

Our study identified that the social categorization of focused and diversified individual profiles within entrepreneurial teams are critical determinants of new venture performance. The presence of focused profiles in individuals can have an independent positive impact on R&D and commercial venture outcomes. This finding supports prior studies that the combination of human capital characterized by depth of expertise and breadth of information and knowledge connections are important in the development of small entrepreneurial firms (Jansen et al., 2011). In contrast, diversified profiles only play a significant role when combined with focused profiles. This finding is supported by the study of Gruber et al. (2012), which found that entrepreneurial generalists who have access to the expertise of functional specialists perform better in market opportunity identification than on their own.

The results of testing effects of within-team configurations indicate that when a diversified team member assumes the scientific role, the venture is likely to focus more on invention rather than commercialization. A potential explanation is that scientists with a diversified profile are likely to recognize novel ways and multiple possibilities in which their ideas may succeed and therefore generate unconventional and transformative scientific ideas (Berg, 2016), which are likely to result in patentable inventions. Conversely, when a diversified team member assumes the managerial role, the venture is likely to focus more on commercialization than on invention. This is broadly consistent with the findings that diversified human capital facilitates access to a wider opportunity set (Gimeno et al., 1997). Managers typically enter the creative process at the stage of evaluation and selection of commercial opportunities. Hence, a potential explanation behind our finding is that diversified managers are likely to have a well-developed market visioning competence (Reid & De Brentani, 2015), reflected in their ability to link advanced technologies to market opportunities of the future (O'Connor & Veryzer, 2001) and to successfully anticipate the market acceptance of the commercial products based on new technological advances (Dimov & Shepherd, 2005, p. 16). Diversified managers are likely to deviate from the current understanding of technological products and their applications (Reid & De Brentani, 2015) while looking for a profitable niche to exploit the technological idea proposed by a scientist on a team. Therefore, when assuming a managerial role, diversified individuals are able to exhibit a customer-, profit-, and market-oriented approach to the selection of opportunities (Mathias & Williams, 2017).

Our results have practical implications relevant to managers and entrepreneurs, public policy makers, and public value. Establishing "ideal" science-focused entrepreneurial teams and R&D teams in small firms is challenging. These entrepreneurial team members need to assess first what social categorization they identify with - be it focused or diversified. Although members with focused profiles can have a significant individual contribution to both innovation-related and business-related team outcomes, their performance is significantly enhanced when combined with members with diversified profiles. We therefore suggest that the role of a diversified member fundamentally determines the strategic orientation of a team. Consequently, *teams seeking to enhance their R&D outcomes should seek diversified principal scientists*, whereas *teams looking to commercialize should appoint diversified managers*. By the same token, diversified team members may bypass their own shortcomings and complement their strengths by attracting team members with focused human capital profiles.

As such, our findings support social categorization, which potentially allows for ex ante profile analysis by public policy makers to assess the nature of leadership within an entrepreneurial team while assessing funding opportunities. Depending on the form of focused or diversified social categorization that scientists and managers identify as, different opportunities will lead to manifestly different implications (Mathias & Williams, 2017, p. 892). This suggests that the role of a diversified profile, which reflects a prototypical entrepreneurial competence (Silva, 2007), is pivotal in determining the trajectory of a new venture, and investors in the form of public policy makers employing public funds should be aware of this. Simply put, the role that an entrepreneur assumes within a team can define the course of venture's development. Therefore, while the combination of focused and diversified profiles is necessary for the success of entrepreneurial teams, diversified profiles within small science-based and research-intensive firms should be viewed as an important factor defining whether a venture has a research or commercial orientation. Therefore, our findings extend the prior inquiry into the influence of top management team composition in developing a strategic orientation of firms (Díaz-Fernández et al., 2020; Escribá-Esteve et al., 2009).

Overall, *our results imply that access to unique profiles is often insufficient to directly enhance venture performance*. Rather, *it is the specific configurations of profiles that create innovation and value appropriation, which lead to enhanced performance of these new ventures*. Our insights are in line with the finding of Gruber et al. (2012) that the configuration of the founding team endowments has noteworthy influence on opportunity identification outcomes. The authors point out that *"team endowments can be seen to have important synergistic effects: market opportunity identification is driven not only by the endowments of individual members of the founding team but also by the specific ways in which these endowments combine in the founding team"* (Gruber et al., 2012, p. 1440). Accordingly, our investigation provides further evidence on the relevance of moving away from a main-effects-only model toward a more fine-grained interactions and non-linear approach in studying effects of founding teams on venture outcomes (Delmar & Shane, 2006; Patzelt et al., 2008).

### *5.2. Limitations and future research directions*

Beyond the theoretical and practical implications outlined above, we offer several suggestions as to how our study could be extended. First, we operationalized R&D performance as a function of patenting activity of the firm. This construct captures both inventive capacity as well as a strategic inclination to appropriate one's own knowledge by obtaining IP rights for the exclusive exploitation of this knowledge. In industries such as pharmaceuticals and biotechnology, patenting is a necessary process to thrive in the competitive business environment (Markman et al., 2004). However, this raises the issue of how generalizable our findings are to the industries where patenting is less prevalent. Future studies could address this potential limitation by capturing alternative aspects of R&D performance.

The focused and diversified profiles analyzed in our study are just one of many potential conceptualizations of accumulated human capital that might explain the link between entrepreneurial team composition and venture outcomes. To further advance the understanding of this link, future studies can derive alternative relevant conceptualizations and corresponding operationalizations of human capital investments by aggregating the single item constructs into more complex ones and investigating their role as potential mechanisms that influence the value of entrepreneurial skills for enhanced venture performance. By moving beyond studying the aggregate team level relationship of skills underpinning key entrepreneurial roles on venture performance in the direction of pursuing research on the team composition, will help entrepreneurs understand which configurations create a skills-infused form of competitive advantage and which ones do not.

## 6. Conclusion

Our study extends entrepreneurial team composition and human capital streams of literature. We distinguish between focused and diversified profiles and examine how the presence of these profiles underpins two key roles within R&D-focused entrepreneurial teams. We study how focused and diversified profiles are reflected in the roles of a principal scientist and a manager within a team. We test two within-team skill-to-role configurations and show that complex profiles (i.e., focused and diversified) result in superior performance when combined across two team members. Ventures' focus on R&D versus commercial outcomes depends on whether a principal scientist or a manager possesses a diversified profile.

## Declaration of competing interest

No potential conflict of interest was reported by the authors.

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## Appendix. Results of the stochastic frontier model: Estimation of R&D performance

| Ln (Patent applications$_{t+1,\ t+2,\ t+3}$) | Baseline Model |
|---|---|
| Constant | 3.42*** (0.00) |
| Ln (Citation-weighted patent stock$_{t-1}$) | 0.16*** (0.00) |
| Ln (Patent classes$_{t-1}$) | −0.08*** (0.00) |
| Ln (R&D funds$_{t,\ t-1,\ t-2}$) | 0.39*** (0.00) |
| $\delta^2 v$ | −30.43 (189.07) |
| $\delta^2 u$ | 4.37*** (0.10) |
| Wald Chi$^2$ | *** |
| Log Likelihood | −570.20 |

***p < 0.01; **p < 0.05; *p < 0.1; standard errors in parentheses.

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