Received: 30 June 2017 | Revised: 14 June 2019 | Accepted: 18 June 2019

DOI: 10.1002/sej.1331

SPECIAL ISSUE ARTICLE

STRATEGIC ENTREPRENEURSHIP JOURNAL WILEY

Collaboration and informal hierarchy in innovation teams: Product introductions in entrepreneurial ventures

Amrita Lahiri[1] | Emily C. Pahnke[2] | Michael D. Howard[3] | Warren Boeker[2]

[1]Department of Management, Information Systems and Entrepreneurship, Carson College of Business, Washington State University, Pullman, Washington

[2]Department of Management and Organization, Michael G. Foster School of Business, University of Washington, Seattle, Washington

[3]Department of Management, Mays Business School, Texas A&M University, College Station, Texas

Correspondence
Amrita Lahiri, Department of Management, Information Systems and Entrepreneurship, Carson College of Business, Washington State University, Pullman, WA 99163.
Email: amrita.lahiri@wsu.edu

Funding information
Texas A&M University; University of Washington

Abstract

***Research Summary*:** Although stars may be particularly innovative, building teams to collaborate with them can be difficult. Coordinating efforts between stars and non-stars may be especially complex in new venture, which rely on informal hierarchy to manage organizational tasks. We investigate how a venture's success at introducing new products may be influenced by the extent to which company founders and star performers are involved in co-developing new technologies. By analyzing innovation teams within a sector of the medical device industry from 1986 to 2007, we find that combining both star inventors and founder-inventors on a venture's innovation team may limit product introductions. Our results highlight the importance of organizational design in managing coordination and resource allocation in a venture setting and suggest important boundary conditions when stars may impede, rather than benefit, innovation.

***Managerial Summary*:** Designing an innovation team can be challenging for new ventures. While the presence of a technologically proficient founder or highly accomplished inventor can significantly bolster a new venture's innovation efforts, our results indicate that these roles must be carefully managed to prevent conflicts between them. Our findings suggest that founders who hire star inventors should establish a clear hierarchy of decision-making within innovation teams, while also offering greater autonomy to the star inventor in matters concerning innovation leadership and product development. We also suggest that it may be advantageous for founders to hire star inventors with prior experience working in new ventures as opposed to older, established organizations. Overall, our study indicates that new ventures need to exercise caution in hiring and managing star employees.

KEYWORDS
entrepreneurial leadership, innovation, innovation teams, new product development teams, stars

1 | INTRODUCTION

Organizational design choices made during their early years have a long-lasting impact on ventures. New firms must construct their internal structures in ways that will support the development of innovative products, quickly providing revenue, and legitimacy while establishing the venture's future viability. Past research has shown how coordinated team efforts create innovations that can lead to successful product introductions (Hargadon, 2002; Matusik, 2002; Taylor & Greve, 2006) and has highlighted the importance of this team, variously labeled the inventive team (Bercovitz & Feldman, 2011), creative team (Reagans & Zuckerman, 2001; Roberts, 1991), or innovation team (Knight, 1989; Nerkar, McGrath, & MacMillan, 1996) to new venture success. The manner in which the new venture's innovation team[1] (the term we adopt here) is organized can have important implications for the innovation success of the firm.

Although the importance of the innovation team for the new venture's success is well-established (Beckman, Burton, & O'Reilly, 2007), many questions remain as to how these teams should be configured to enhance their effectiveness (Bercovitz & Feldman, 2011; Chen & Garg, 2018; Onal Vural, Dahlander, & George, 2013). At the firm level, prior research establishes the considerable influence of founders and founder backgrounds on organizational design. Founders with broader functional experience create greater opportunities for growth and success (Beckman & Burton, 2008), and higher founder human capital may set the stage for the more rapid emergence of hierarchical structure and greater administrative intensity (Baron, Hannan, & Burton, 1999; Colombo & Grilli, 2013). By choosing to keep tight control over the firm, founders may ultimately even undermine its value (Wasserman, 2017).

Founders must determine how to organize the innovation effort, specifying the roles that key members of the innovation team should play and how decisions regarding new product introductions are made. These choices are likely to be particularly challenging and impactful when managing star performers (Chen & Garg, 2018). Prior research has shown that there is a significant positive impact of highly accomplished individuals or “stars” on team innovation, reinforcing the intuitive notion that these members may make a team more innovative (Toole & Czarnitzki, 2009; Tzabbar & Kehoe, 2014; Zucker, Darby, & Armstrong, 2002). However, as Chen and Garg (2018:

p.1240) note, "[Organizations] face a tradeoff in utilizing stars. On the one hand, stars possess unique skills and bring new ideas to the organization. On the other hand, these unique skills may also make it difficult for organizations to use stars effectively because organizational routines are typically geared to utilize more conventional skill sets". Founder characteristics, choices and consequences extend to the strategy and design of the innovation team (Eesley, Hsu, & Roberts, 2014; Ott, Eisenhardt, & Bingham, 2017), illustrating the critical nature of these early organizational decisions.

While established organizations typically have existing routines and formal hierarchy for managing organizational tasks, new ventures are more likely to rely on informal hierarchy—an implicit rank ordering determined by the extent to which they defer to each other's individual expertise and competence (Freeman, 1986; Magee & Galinsky, 2008; Sørensen, 2007). However, the extent to which this informal hierarchy is understood and agreed upon is likely to vary (Blau, 1977). For example, some teams may be implicitly organized based on social affinity, while others may be based on their task expertise. When members of an innovation team derive their prior successes and standing within the team from different sources there is likely to be less clarity and agreement among members as to whom should be deferring to whom (He & Huang, 2011). As we suggest in this study, this ambiguity can impair the ability of the venture to successfully innovate. In particular, we explore the challenges to ventures that configure their innovation teams such that star inventors, who have already amassed an extremely successful record of accomplishment of innovation, collaborate on invention with company founders, who are often originators of the initial ideas that led to the firm's creation. Organizations face a tradeoff in utilizing stars. On the one hand, stars possess unique skills and bring new ideas to an organization. On the other hand, these unique skills may also make it difficult for organizations to use stars effectively because organizational routines are typically geared to utilize more conventional skill sets.

Our research is motivated by whether configuring teams to bring together individuals with expertise derived from different sources can actually lead to subpar outcomes for the firm. For example, highly accomplished team members may have a detrimental effect on innovation if competition among them undermines their ability to work together effectively (Loch, Huberman, & Stout, 2000). Recent research has demonstrated how star performers may have trouble collaborating effectively (Chen & Garg, 2018; Groysberg, Polzer, & Elfenbein, 2011) or may engage in unproductive status-seeking when there are too many of them (Overbeck, Correll, & Park, 2005) or when group members hold differing perceptions of the informal hierarchy of expertise on the team (Kilduff, Willer, & Anderson, 2016).

The empirical context of our study is the minimally invasive surgical device (MIS) segment of the US Medical Devices industry, a quintessential example of an industry driven by innovation and entrepreneurship. We examine the industry from its inception in 1986 through 2007, tracking all new ventures over this history. By setting our study in a population of new ventures that are initially focused on the creation and launch of a single product, we are able to identify the innovation team members (Gruber, MacMillan, & Thompson, 2012). We examine the role of two types of team members on product introductions in these new ventures: (a) founder-inventors—founders of the new venture who also engage in patenting for the venture they start and (b) star inventors—extraordinarily productive individuals whose past innovative output places them among the top 5% of all inventors in the industry.

Our findings suggest that the presence of star performers and founder-inventors on a firm's innovation team is positively associated with improved firm performance. Surprisingly, combining founder-inventors and stars on the team may actually limit successful product introductions. Our post-hoc analysis suggests that this outcome is likely a result of a lack of innovation leadership within the venture arising of the informal organizational hierarchy. Our study makes several contributions. First, we inform the literature on innovation in new ventures by exploring how entrepreneurial ventures' internal organization shapes innovative performance. Specifically, we contribute to further understanding how individual expertise and hierarchical structures act together to promote or limit the efforts of innovation teams, highlighting some of the boundary conditions around the benefits that star performers can provide for innovation. In doing so, our study extends an emerging body of evidence (e.g., Chen & Garg, 2018; Groysberg, Lee, & Nanda, 2008; Kehoe & Tzabbar, 2015) that suggests that there are also significant challenges in managing highly productive individuals within organizations. Second, we extend recent research on the effects of informal hierarchy among group members (He & Huang, 2011; Kilduff et al., 2016) by showing how ambiguous hierarchies may undermine the ability of the new venture to innovate successfully. Finally, our research contributes to and extends understanding of how an important aspect of organizational design, the makeup of the innovation team (cf., Conti, Gambardella, & Mariani, 2014), has important consequences for the venture's subsequent success in introducing new products.

2 | THEORY

Innovation is often defined as "a process that begins with an invention, and results in the introduction of a new product, process or service to the marketplace" (Edwards & Gordon, 1984; Katila & Shane, 2005). In this view, the introduction of a product is the ultimate outcome of the innovation process, which typically begins with the development of novel inventions documented in patents and then proceeds through various product development stages, such as prototyping, testing for efficacy, and in our setting, clinical trials. The knowledge used in these processes is often tacit and resides in individuals (Simon, 1991), necessitating collaborative interactions and relational ties (Polanyi, 1966). For example, Guimerà, Uzzi, Spiro, and Amaral (2005) argue that organizations create teams specifically to combine individuals with different capabilities, knowledge, and skills, who can then work together to augment their individual innovation efforts. The technological backgrounds of the individuals on the team and the ability of the team to productively collaborate can determine the success of the firm's innovation efforts (Bercovitz & Feldman, 2011).

Assembling an effective innovation team has been shown to be a difficult task for many firms (Guimerà et al., 2005; Onal Vural et al., 2013). When the goal is to introduce a new product, ventures need to achieve the integration of individual expertise within a team context to ensure the success of their innovation efforts (Ancona & Caldwell, 1992). Achieving this integration may be particularly challenging in teams where stars and non-stars collaborate (Chen & Garg, 2018). Although the literature on star performers has drawn attention to the potential benefits arising from their collaborative capability (Kehoe & Tzabbar, 2015; Oettl, 2012; Taylor & Greve, 2006), scholars have also argued that, given the social and interdependent nature of knowledge creation, an organization's ability to leverage a star's unique skills can be "an exercise in learning under complexity," involving "numerous trial and error adjustments" (Chen & Garg, 2018: p.1241). Given the importance of organizing innovation teams in a way that actually allows firms to capture their value (Conti et al., 2014; Reagans, Argote, & Brooks, 2005), we study the organization of invention activities of star inventors and company founders in newly founded organizations.

2.1 | Team member quality and informal hierarchy

The success of innovation teams in new ventures depends on the participation of competent team members. In team settings, members form beliefs about each other's competence and expertise, and such beliefs result in an informal hierarchical ordering that influences how team members work together (He & Huang, 2011). As Magee and Galinsky (2008) note, the creation of an informal hierarchy can occur in a wide variety of settings, including work groups (Groysberg et al., 2011), fraternities (Gould, 2002), and even street corner gangs (Whyte, 1943). This informal hierarchy can help facilitate and clarify decision-making (He & Huang, 2011), including decisions around the technological direction of the venture. Team members who are viewed as more competent or successful are likely to have a prominent role in these decisions. Through the active involvement of highly accomplished individuals in the founding of the firm and the innovation process, the new firm can enhance its legitimacy (Higgins & Gulati, 2003) and attract additional resources from resource providers (Certo, 2003), benefiting the firm financially as well as improving its access to timely information regarding technology developments in the industry.

2.1.1 | The role of star performers

Recruiting expert employees is one way for new firms to help ensure their survival (Wasserman, 2012). A rich body of research has emphasized the important role that star performers play in innovative organizations (Baba, Shichijo, & Sedita, 2009; Hess & Rothaermel, 2011; Zucker et al., 2002), where "stars" are defined as extraordinarily productive individuals who achieve distinction in their respective fields (Chen & Garg, 2018; Kehoe & Tzabbar, 2015; Subramanian, Lim, & Soh, 2013; Zucker et al., 2002). Although hiring stars is often expensive (Groysberg et al., 2008; Groysberg et al., 2011), new ventures may consider such investments worthwhile for several reasons. Most obviously, since stars have succeeded in the past, they are typically expected to do so in the future and may help ensure the success of the new venture. For example, stars may have prior experience understanding and successfully addressing problems with the product development process and may be aware of how to overcome these problems.

Stars may be especially valuable to new ventures lacking a history of success and tangible accomplishment. For example, stars may help to legitimate a new venture (Benjamin & Podolny, 1999), thereby helping to recruit other key personnel and resources (Hess & Rothaermel, 2011; Lacetera, Cockburn, & Henderson, 2004). In the new venture setting stars can provide alignment and direction and their position in the informal hierarchy (and the attendant deference accorded them) may help focus the team more quickly around a set of problems and solutions (Johnson, Funk, & Clay-Warner, 1998). A star inventor's leadership can help a team avoid many of the costs of undirected exploration and better orchestrate team members' technological expertise to rapidly develop successful products and secure their intellectual property rights through patents (Tzabbar & Kehoe, 2014). For example, stars may have mental models of efficient ways of testing the efficacy of a new medical device, or connections to industry experts who can help identify potential problems at an early stage. Such a focus is particularly important to resource-constrained new ventures that cannot afford costly missteps, and for which product introduction is a key means of gaining legitimacy and revenue (Schoonhoven, Eisenhardt, & Lyman, 1990). Given the voluminous amount of past research that has demonstrated the importance of stars for innovative efforts, our baseline assumption is that new ventures with more stars on their team will be more likely to introduce new products.

2.1.2 | The role of hierarchical position

In contrast to a position in the *informal* hierarchy based on technical expertise, such as for star inventors, the stature of innovation team members may instead be obtained and evaluated based on their position in the organization's *formal* hierarchy (Dahlander & McFarland, 2013; Gould, 2002). Founders occupy positions of influence within a start-up firm that may transfer to their role within the innovation team. Research by Wasserman (2003) demonstrates how the founders of a venture can have an extraordinary influence on the key decisions made within the firm. Founders that also have technical expertise and participate on the innovation team are likely to be accorded deference based on their positions both in the formal and informal hierarchy (Gruber, MacMillan, & Thompson, 2013), and past research has demonstrated that greater founder human capital is associated with more rapid formation of hierarchical structure in a new venture (Colombo & Grilli, 2013). Founder-inventors have substantial discretion and greater freedom to allocate resources such as funding and personnel to projects they find especially promising. Given their discretion and influence, founder-inventors are able to coordinate the actions of the innovation team and focus attention and resources toward projects in which they are actively involved. Such direction by founder-inventors is likely to increase other team members' support of specific projects or approaches, facilitating better collaboration (Bercovitz & Feldman, 2008). Therefore, the active participation of founders in technology development is likely to improve product introduction in new ventures by directing knowledge development efforts, enhancing legitimacy, and increasing resources. Our second baseline assumption is that new ventures with active founder-inventors will be more likely to introduce new products.

2.2 | Deference among inventors

A star inventor or a founder-inventor might expect to play a critical role within the innovation team, commensurate with her accomplishments and importance to the innovation efforts of the venture. However, some level of dysfunction may occur when a star inventor and a founder-inventor work together on the same innovation team, due to the fact that each of them draw their standing from different sources (Magee & Galinsky, 2008). Consider a situation where members of an innovation team can be clearly ordered based on their accomplishments such that the informal hierarchy is clear. This informal hierarchy creates a straightforward social order in which the ideas and opinions of higher-ranking team members are likely to be respected and followed more than those of lower-ranking team members. In turn, this may lead to more clarity and agreement on the technological direction of the venture (He & Huang, 2011).

In contrast, in a group where many members each see themselves as accomplished experts, some members may need to subordinate their own views in order to maximize the performance of the group (Hogan & Hogan, 2002). Problems may arise in such situations because these accomplished individual team members have different views about the technological direction of the venture and may be less willing to engage in compromise or integrative actions in order to further the work of the team (Hambrick, 1994). When no established hierarchy exists among team members, group interactions tend to "become confusing, inefficient, and frustrating," and coordination suffers (Magee & Galinsky, 2008: p.357). Ridgeway and colleagues (Ridgeway & Johnson, 1990; Ridgeway, Johnson, & Diekema, 1994) demonstrate that task groups that lack differentiation in the informal hierarchy also lack a sense of group solidarity, leading to negative emotional reactions and poorer performance. For example, Groysberg et al. (2011) in a study of investment banks, found that having multiple high-status analysts within a research department had a diminishing and ultimately negative effect on performance.

Within innovation teams, leadership is typically assumed by the individual who is considered an expert in that specific domain (Tzabbar & Kehoe, 2014; Zucker, Darby, & Armstrong, 1998). Innovation leadership, in this context, can be defined as, "the ability of a firm's members to initiate and lead innovation" (Kehoe & Tzabbar, 2015: p.711). Stars working in innovation teams are typically expected to lead the research agenda for that team (Kehoe & Tzabbar, 2015). On the other hand, founder-inventors are empowered with a great deal of discretion and control over the firm's resources and its technological direction (Park & Tzabbar, 2016). Foundational work on social theory in organizations has long argued that sources of importance or influence based on different criteria can be detrimental for performance (Scott, 1966; Stinchcombe, 1959; Udy, 1959). For example, it is difficult to compare achievements in technological development or influential journal publications with a work history of important managerial positions at prominent firms. Consequently, performance across different dimensions may not be easily reconciled to determine a clear hierarchy of authority, which may lead to uncertainty and unproductive debate within the innovation team. With greater uncertainty about relative standing among members of the group, individuals tend to revert to beliefs that their own position surpasses that of others (Berger, Cohen, & Zelditch Jr, 1972; Berger, Ridgeway, Fisek, & Norman, 1998). In firms where founders and stars work together on innovation activities, this uncertainty can lead to ambiguity in innovation leadership.

Firms can vary in the extent to which founder-inventors and star inventors collaborate. Collaboration between founder-inventors and stars on innovation activities will necessitate negotiation and coordination on the innovation targets and activities to be performed by the firm. Firms where most innovation efforts involve collaboration between founder-inventors and star inventors could indicate less delegation of innovation efforts by the founder-inventor and could be at greater risk of negative consequences from poorer task coordination (Magee & Galinsky, 2008). Further, collaboration efforts with founders may limit the scope of search engaged in by the star for a specific innovation effort as they would need to discuss and negotiate any innovation goals with the founder along with the best way to achieve the goal (Azoulay, Graff Zivin, & Manso, 2011; Conti et al., 2014). However, firms where innovation efforts can be independently led by founder-inventors or star inventors without necessitating joint collaboration are likely to result in a better balance of innovation leadership in the firm, with such teams more likely to achieve successful innovation outcomes. We argue that greater collaboration around innovation between founder-inventors and star inventors may create greater challenges in bringing innovations to market for the new venture, thus delaying the launch of new products.

Hypothesis 1: *Firms with a greater proportion of their innovation activities performed jointly by stars and founder-inventors will have fewer product introductions*.

2.3 | Knowledge domains of founders and stars

The detrimental impact of the simultaneous presence of stars and founder-inventors on a venture's innovation team may vary depending on the knowledge base from which each of them draws in the course of developing innovations. Given that new ventures with no history cannot draw from a rich organizational knowledge base accumulated through years of operating experience, the simplest approach is to exploit and pursue knowledge in areas with which the founders are familiar (Chatterji, 2009; Stuart & Podolny, 1996). Exploiting knowledge domains familiar to the founders enables the venture to leverage existing knowledge and build on routines that may have worked well in the past (Park & Tzabbar, 2016; Winter, Cattani, & Dorsch, 2007). However, research suggests that star inventors, given their past success, are more likely to innovate at the new venture in ways that build on *their* own expertise. As Tzabbar and Kehoe (2014) note,

"Due to individuals' cognitive limitations (March & Simon, 1958), an interest in sustaining their unique positions within the firm (Pfeffer, 1981), and preferences for predictability in performance (Audia & Goncalo, 2007), stars are likely to prefer that a firm continues to focus on research activities and technological niches that require their expertise, and thus are likely to prefer exploiting their own research agendas" (p.455).

Within the context of a new venture's innovation team, the extent of technological knowledge similarity between founder-inventors and star inventors is likely to have important implications for the venture's success in generating innovations (e.g., Basu, Sahaym, Howard, & Boeker, 2015). Having similar knowledge domains would indicate that the founder-inventor and star inventor are likely to have a similar understanding of how technologies work and are likely to look for new solutions in a neighborhood familiar to both (Cohen & Levinthal, 1990; Fleming, 2001). When the technological knowledge domains of the founder-inventors and star inventors are similar, they are likely to have a higher capacity to leverage their mutually shared knowledge to further the firm's innovation goals. However, too high levels of knowledge similarity between the founder-inventor and the star inventor may lead to greater ambiguity in innovation leadership, potentially leading to disagreements on the technological direction of the venture, thereby adversely affecting the firm's ability to introduce new products. For example, Dahlander and McFarland (2013) find that greater overlap in the knowledge domain across scientists leads to lower likelihood of collaboration and shorter duration for the collaborations that do exist. Indeed, as noted by a founder in the popular press, "Smaller businesses tend to attract take-charge types who like to try new things, and roles within a startup often overlap by necessity. When that tension escalates to an all-out turf war, it can destroy your business from the inside" (Gerber, 2014).

Conversely, we suggest that if the areas of technological expertise between the founder-inventor and star inventor are too dissimilar, it may be difficult to successfully integrate the knowledge areas of the star inventors and founder-inventors and successfully produce innovative products. This is based on the argument that the absorptive capacity of an individual or firm is principally grounded in their existing base of knowledge (Cohen & Levinthal, 1990; Mowery, Oxley, & Silverman, 1996). When the knowledge similarity between founder-inventors and star inventors is too low, they are likely to have a lower capacity to leverage their mutually shared knowledge to further the firm's innovation goals (Ahuja & Katila, 2001; Dosi, 1988). Thus, both too high and too low a level of similarity between the knowledge domains of the star and founder-inventor can have a negative effect on product introductions by the new venture.

In sum, a certain degree of divergence between the technological knowledge domains of founders and star inventors is often desirable; however, there are declining returns to such divergence. By combining the more familiar knowledge domains of founders with the potentially dissimilar knowledge areas of star inventors, new ventures can more successfully create new knowledge that leads to the introduction of new products (Tushman & O'Reilly, 1996). Thus, we expect that new ventures will be most effective at introducing new products when a founder's own technical expertise diverges from the knowledge domains of the star inventor to some degree but not when this difference is too high.

> **Hypothesis 2:** *The degree of similarity between the founder's and star inventor's technological knowledge domains has an inverted U-shaped effect on product introductions by the venture.*

3 | METHODS

3.1 | Sample and data sources

We focus our study on startups in the minimally invasive surgical devices (MIS) segment of the medical device industry. These devices can radically improve patient outcomes by allowing for small incisions during surgical procedure. Medical histories trace the origins of the industry to the mid-1980's, with the first companies focused on developing these devices founded in 1986 in the U.S. (Park & Lee, 2011). MIS devices are technologically complex and typically encompass multiple underlying patents. The protection of intellectual property via patenting is a vital part of the product development cycle in this industry and innovation and collaboration can be observed through the patenting record (Cohen, Nelson, & Walsh, 2000; Graham, Merges, Samuelson, & Sichelman, 2009). An important feature of our focus on startups is that the notable ways in which they organize Research and Development (R&D) projects differs from R&D in established companies; this is particularly evident in the MIS industry for several reasons. First, many medical device firms are founded by surgeons, who recognize the need for a specific device, which is related to their personal experience and expertise (Smith & Shah, 2013). They then found a company to pursue the development of this device. Typically, this focus persists at least until FDA approval is obtained. This contrasts with established medical device firms that develop many, often unrelated, product lines, and technologies simultaneously. Second, developing these devices is costly and takes several years. Unlike established companies that have considerable resources to pursue multiple, unrelated projects simultaneously, resource-constrained new ventures rarely have the financial ability to pursue many concurrent R&D projects. Thus, our focus on new ventures enables us to draw clearer causal inferences compared to large firms where many R&D projects are pursued simultaneously. Third, unlike the rigid hierarchical structures and divisions that often exist in established organizations, the organizational structure in startups is much flatter, which allows us to more precisely observe inventors that participate in specific projects. As a result, when we observe the activities of inventors in our study, we are confident that they are involved in the core R&D effort of the new venture, and the result of their participation should directly influence product introduction outcomes for the firm.

Our data collection began by interviewing over 40 MIS device experts including VCs, entrepreneurs, regulators, engineers, surgeons, medical professors, and consultants. Interviews lasted between 30 and 90 min and consisted of open-ended questions about the participant's role in the industry. We asked entrepreneurs and engineers questions about their role in inventing and commercializing new product devices. These interviews helped us develop our data collection strategy and identify industry-appropriate measures. They also provided insight into the product development process and industry dynamics and aided in validating our theory. The MIS industry is a distinct subclass of medical devices in the minds of those involved in the industry. However, it is not clearly delineated by patent classes or SIC codes. To examine the population of all United States firms in this industry, we compiled data from numerous sources including survey data from Windhover Information Inc., (an industry intelligence firm) and membership lists and conference proceedings from trade organizations (e.g., The International Society for Minimally Invasive Cardiac Surgery and The Medical Device Manufacturer's Association). We also used the National Institute of Health's Medical Subject Heading (MESH) classification scheme to identify words associated with MIS devices, which we then used to search LexisNexis and Google to identify individual startups. After identifying firms in the industry, we collected data on company founders. These data were compiled from numerous sources including the firm's own websites, archives of the firm's websites (htttp://www.archive.org/), ZoomInfo, Business Week, LinkedIn, and LexisNexis. Although we collected data on the entire population of U.S. based firms in the industry, we restrict our analysis to firms that filed a patent, attempted to develop an MIS device (not manufacturers or distributors), and were independently founded (i.e., not spinoffs) between 1986 and 2007, and for which we were able to find data on the founding teams.

We start the sample in 1986, which is when our industry informants and medical industry experts indicate the first firms were founded to develop MIS devices. We matched this data with information on patents associated with the new venture. We then created a comprehensive data set of all patents that were filed and subsequently granted by firms in our data set. To create this data set, data on patents and inventors were triangulated across both the Delphion database and disambiguated inventor data obtained from Harvard Dataverse (Li et al., 2014). For every inventor associated with these patents, we created complete inventor histories that enabled us to track their collaboration histories longitudinally, building on previous studies, which utilized patents to measure inventor team characteristics (Paruchuri, 2010; Phelps, 2010; Singh & Fleming, 2010). Data on patents extends from 1976 to 2010, providing an adequate period in which to observe subsequent patenting activity of the new ventures. Since many of our variables of interest rely on patent data, we limited our sample to firms that have at least one patent in the first 5-years following the founding date. This constrained our sample to 132 firms.

Our study is at the firm level and examines the interaction between the founder-inventor(s) and star(s) for each new venture in our data sample. This team consists of all individuals in the firm who actively participate in developing the firm's technology, as documented in the patent record. The 132 firms in our final sample included data on 87 stars, 195 founders, and 93 founder-inventors (most firms have multiple founders), 2,205 inventors, and 3,346 unique patents over the observation period. We performed *t*-tests to understand how these firms might differ from the entire population (i.e., those firms that did not patent or for which we could not find founder data) and found no significant differences in terms of number of founders, firm financing, or founder experience variables.

3.2 | Measures

3.2.1 | Dependent variable

MIS devices cannot be sold in the U.S. without first receiving FDA approval (Chatterji, 2009). The date of an FDA approval is a good proxy that indicates when a product was released to the market. Our dependent variable, *product introductions*, is measured as the focal venture's count of products receiving class III device approval from the U.S. Food and Drug Administration each year. Data on all product approvals were gathered from the FDA's publically available databases.

3.2.2 | Independent variables

Star inventors: "Stars" have been conceptualized as extraordinarily productive individuals who achieve distinction in their respective fields (Chen & Garg, 2018; Kehoe & Tzabbar, 2015; Subramanian et al., 2013; Zucker et al., 2002). For example, Zucker et al. (1998) studied stars in the biotech industry and found that the top 0.75% of contributors accounted for almost 17% of all contributions to the genetic sequence database, GenBank. Other research defines stars in terms of those who are both the most productive and whose work has the greatest impact (Azoulay, Graff

Zivin, & Wang, 2010; Rothaermel & Hess, 2007). To identify star inventors within our sample for a given year *t*, we identified individuals that were in the 95th percentile of inventors based on total number of patents they filed through year *t*, across all the companies in our sample. Our approach ensures that we are able to observe inventor productivity through the course of the development of the MIS industry. We found 88 unique stars in our sample based on this procedure. The average star inventor in our sample was granted 60 patents in the course of his or her patenting history prior to new venture founding. We then created a binary variable (*star*) that was set to one if the focal firm's innovation team contained one or more active star performers and zero otherwise.

Founder-inventor: We created a binary variable (*founder-inventor*) which was set to one if one or more of a venture's founders were actively involved in patenting for a focal startup and zero if they were not. In order to identify firm founders among active inventors in a new venture, we first used a disambiguation algorithm to identify unique inventors (Li et al., 2014) among the founders in our data. Our algorithm draws primarily from the founder's prior organizational affiliation available through our compiled founder profile information. We used this information to rank unique inventor matches by comparing the prior patenting history of a given inventor with the known prior organizational affiliations of that individual. We also manually verified each match using additional information from the founder biographies we compiled. This process allowed us to identify all founders who had engaged in invention activities in the past. In order to identify founders who continued to be actively involved in patenting after founding their company, we used the established unique inventor identity of each founder to determine whether he or she was named on a patent that was filed after the founding date of the new venture.

Proportion of founder-star coinvention: The extent of founder-inventor and star collaboration on innovation activities within a firm in a given year was captured through a time-varying measure. This was the count of annual patents filed by the focal new venture that listed both a founder and star as coinventors, divided by the total number of annual firm patents filed that year.[2] This variable was lagged by a year because the trend in our data shows that product introductions lag patents.

Founder-star technological distance: The degree of similarity between the founder and star's knowledge base is measured based on the technology areas of their patents during the 5 years prior to the founding date of the new venture. By using data on patents in the 5-year period prior to the new venture's inception, we capture their most recent and relevant knowledge base. We measured this construct (*founder-star tech distance*) as the Euclidean distance between patent classes following the approach of Rosenkopf and Almeida (2003). For a specific patent class *i*, this measure was defined as:

$$\left[\sum_i \left(\textit{star patent proportion}_i - \textit{founder patent proportion}_i\right)^2\right]^{1/2}$$

The results are then scaled to provide a range from zero to one, with values close to one reflecting high technological distance between the founder's and the star's knowledge base. For firms that had multiple founder-inventors or multiple stars involved in patenting activities, we considered the maximum distance between each founder-star dyad.[3] Although firms with multiple founder-inventors and stars are a minority in our sample (only five firms fall into this category), Figure 1 demonstrates how this distance would be calculated for a hypothetical firm with two founder-inventors and two stars. In this example, the founder-star technological distance will be calculated as:

$$\mathrm{Max}\left(D_{F1S1}, D_{F1S2}, D_{F2S1}, D_{F2S2}\right)$$

3.2.3 | Control variables

We included a number of control variables in our analyses. New venture innovation outcomes are likely to be affected by the amount of resources at the disposal of the new venture (Kortum & Lerner, 2000). We collected data

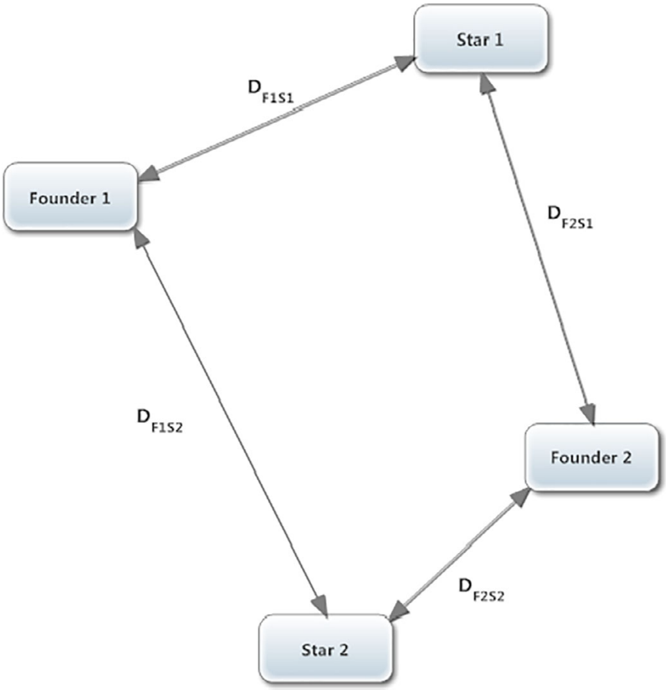

FIGURE 1 Calculation of founder-star technological distance for a hypothetical firm with two founders and two stars

on the financial resources that each MIS venture obtained annually from venture capitalists, corporate venture capitalists, and the government. These data were obtained from VentureXpert, VentureSource, and the government's SBIR program. The net total was captured in the variable *total funding*. This process enabled us to control for performance differences due to heterogeneity in financial resources between firms. The variable was lagged by 1 year in order to account for response time for the funding to impact performance and transformed to account for skewness in its distribution by using the logarithm of the original value. The age of the firm may account for heterogeneity in the extent of legitimacy earned by new ventures, with older firms having more time to establish themselves. This was captured in the variable *firm age*, also lagged by 1 year. The introduction of new products may be directly influenced by a firm's engagement in inventive activities demonstrated by the number of patents filed. Thus, *patent count* controls for the number of patents filed by a firm, lagged by 1 year. As more prominent venture capital firms might plausibly provide superior contacts, expertise, and resources to their target firms (Stuart, Hoang, & Hybels, 1999), we also controlled for heterogeneity of resource providers by tracking whether the firm had a high status venture capital investor, coded as the variable, *VC status*. This binary variable is set to one if the firm received investment from one or more of the top 30 VC organizations in terms of their eigenvector centrality within the VC co-investment networks in technology industries (Bonacich, 1987; Katila, Rosenberger, & Eisenhardt, 2008). Differences in regional ecosystems could affect the firm's ability to innovate. Hence, we control for geographical factors related to firm location by including binary variables if the firm was located in the *Bay Area*, *Orange County*, *Boston or Minneapolis*, and *New York/New Jersey/Connecticut*—five regions noted for medical device innovation. Henceforth, we refer to these geographical controls as *location dummies*. We also include dummies representing the primary competitive subsegment associated with each firm that allowed us to control for heterogeneity across subsegment dynamics within the MIS industry (Pahnke, McDonald, Wang, & Hallen, 2015).

We also control for several factors related to founding team. We control for the size of the founding team (*number of founders*). In addition, we control for the technological distance between founder-inventors and non-star inventors by incorporating a variable *founder non-star tech distance* that measures the Euclidean distance between the founder-inventor and the non-star inventors in the innovation team following the procedure previously described for the creation of the variable founder-star technological distance.[4] We also separately controlled for the number of founder-inventors in the focal firm *(founder-inventor count)*.

We included several controls for heterogeneity in founder-star dynamics. To control for founder and star pre-founding ties, we incorporated a dummy variable *(founder-star common employer)* that was set to one if the founder and star had a common prior employer. Shared ties through prior experience at industry incumbent firms may influence the knowledge base and interactions between innovation team members (Klepper & Sleeper, 2005). We also included a control for the observed time of star entry into the firm by including a dummy variable *(star entry)* that was set to one for the first year when star patenting activity was observed in the firm. Stars that were most recently employed by older organizations are likely to be more attuned to formal hierarchy than stars who were most recently employed by younger organizations. We thus created a binary variable *star origin* that was set to one if the firm had at least one star who was most recently employed by an older organization (at least 20 years-old) (McDougall & Robinson, 1990) based on the patent assignment history of the star inventor. Since firms self-select into hiring stars, the factors that enable firms to hire stars are endogenous to the firm and may be associated with performance achieved (and observed). We discuss our approach to dealing with this potential endogeneity in the next section.

We also controlled for the number of active inventors in a firm (*team size*) as larger teams have both broader and deeper knowledge from which to draw. We did this by including a count (2-year moving average) of inventors who are active in patenting for the new venture. Teams can also vary in the extent to which members share collaboration ties based on their patenting history. To consider this in our analysis, we include controls for the innovation team's *clustering coefficient* and *team density* (Newman, Watts, & Strogatz, 2002), calculated as a 2-year moving average. In calculating the clustering coefficient for a venture's innovation team, we considered the nodes to be individual members of the firm's innovation team. Two nodes were considered to be connected in a given year if the two focal members of the firm's innovation team had collaborated on a patent filed in any period before that year based on their prior patenting histories. The clustering coefficient for a firm's innovation team in a given year was calculated as follows:

$$\text{Clustering} = 3*(\text{The number of triangles in the graph})/(\text{number of connected triples})$$

Here, a triangle is a set of three nodes, each of which is connected to *both* the others. A connected triple is a set of three nodes where *at least one* is connected to both the others. The overall clustering coefficient thus calculated quantifies the extent to which members of a firm's innovation team had a prior history of collaboration with each other. This measure varies between zero and one.

The density of the firm's internal collaboration network for a given year was calculated by dividing the number of actual connections among members of the firm's innovation team in a given year based on their prior history of collaboration prior to the focal year, by the maximum number of potential collaborations among team members.

3.3 | Statistical methods

The level of analysis used in our study is the firm-year, with the data organized as a panel consisting of 1,158 observations from the 132 firms in our final sample. In our study, the presence of star inventors on the innovation team is not exogenous. Firms may hire star performers with the intent of pursuing specific strategies regarding the launch of their initial products. Thus, our empirical strategy was designed to address this issue. We ran our analysis using the system general method of moments (GMM) estimator (Arellano & Bond, 1991). GMM models have several advantages for dealing with challenges in a data set like ours where the dependent variable partly depends on its own prior history, the independent variables may not be strictly exogenous, and where autocorrelation within (but not across) firm level variables is possible (Roodman, 2009). We use the system GMM estimator where the first difference of explanatory variables is instrumented with corresponding levels of lagged variables and the levels are simultaneously instrumented with adequate lagged differences. The system GMM estimator provides an important advantage over the alternative difference GMM estimator, because persistence in the dependent variable (product introductions) can cause severe weak instrument problems in difference GMM models (Roodman, 2009). In our approach, we treat the dependent variable, product introductions, and the proportion of founder-star coinvention as potentially endogenous. Location and year controls were treated as exogenous variables. All other independent variables were treated as predetermined. We follow the recommendation in Blundell and Bond (1998) and incorporate lags of t-2 for all endogenous variables and lags of t-1 for all predetermined ones. A similar approach to addressing endogeneity has been taken by several recent studies (e.g., Berchicci, 2013; Suarez, Cusumano, & Kahl, 2013; Uotila, Maula, Keil, & Zahra, 2009). We use the "xtabond2" routine in Stata 14 to obtain the estimations, which are tabulated in Table 2. To further exclude the possibility of endogenous or unobserved effects confounding our results, we incorporate year dummy variables to absorb any category-invariant heterogeneity occurring within the period of our study. We also use robust standard errors to account for potential heteroscedasticity or serial autocorrelation.

Several tests were used to evaluate the validity of the results obtained. We examine the AR(1) and AR(2) statistics that report the Arellano Bond test for serial correlation in the error terms. Serial autocorrelation is expected in the AR(1) statistic but not in the AR(2) statistic. This assumption is consistent with our finding a non-significant AR(2) statistic. We thus conclude that serial autocorrelation is not present in the error structure. We also test for and report the Hansen's J statistic, with the reported results further demonstrating the validity of the GMM estimates obtained.

3.3.1 | Endogeneity in star selection

As noted earlier in this article, a potential source of endogeneity when analyzing star influence on firm performance is that firms self-select into hiring stars. For that reason, observed firm performance may be conditional on unobserved factors that influence firms' ability to hire star inventors. To correct for this potential bias, we used a two-stage Heckman selection model (Heckman, 1979). Following Hamilton and Nickerson (2003), the first stage of this model is used to specify the selection model, that is, the likelihood of sampled firms to successfully hire star inventors. The results of this stage are used to calculate the Inverse Mills ratio, which is then used as a control variable for the second stage.

4 | RESULTS

Table 1 presents the means, *SD*, and correlations among the variables. As is indicated in the correlation matrix, the presence of stars is significantly correlated with larger teams and a higher number venture patents.

In our first stage probit model, we used the following variables to estimate the likelihood that a firm hires a star: external economic conditions indicated by the year-end closing value of the S&P500 index (logged), founder science professor (binary variable indicating whether any of the founders were Science Professors), founders' industry experience, management experience, and entrepreneurial experience (binary indicators of whether any of the founders had industry-specific prior experience, management experience or had previously founded a medical device start-up), founder education variables (binary variables indicating whether any of the founders had a Ph.D., MBA, JD, or MD) number of firm founders, and the total amount of funding received by the venture. This analysis is tabulated in Table 2. We used the S&P500 index as an instrument that would reflect environmental munificence. The broad market performance of established, publicly traded firms might plausibly influence the opportunity costs of star scientists and their likelihood to pursue the relatively risky path of joining startups, without directly impacting individual firm performance outcomes. Furthermore, this variable met the criteria for "strong" instruments recommended by past research, assessed by the significance of the F-statistics (Bascle, 2008).

TABLE 1 Correlation table[a]

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Product introductions	0.51	1.19	1														
2. Founder-inventor	0.28	0.4	0.2	1													
3. Star inventor	0.26	0.44	0.22	0.56	1												
4. Proportion of founder-star coinvention	0.03	0.14	0.01	0.31	0.35	1											
5. Founder-star tech distance	0.32	0.31	0.02	0.14	0.05	0.01	1										
6. Founder-star common employer	0.11	0.31	0.02	0.09	0.14	0.2	−0.13	1									
7. Founder-inventor count	1.24	0.94	0.02	0.28	0.12	0.15	0.19	0.26	1								
8. Star origin	0.25	0.44	−0.06	−0.09	−0.21	−0.19	−0.12	−0.07	−0.08	1							
9. Star entry	0.04	0.19	0.02	0.18	0.31	0.22	0.01	0.08	0.02	−0.1	1						
10. Firm age	7.01	4	0.04	−0.01	−0.04	0.06	0.02	0	−0.02	0.08	−0.06	1					
11. VC status	0.15	0.35	0.07	0.14	0.2	0.08	−0.06	0.02	0.02	0.07	0.15	−0.13	1				
12. Total funding	0.82	6.43	0.06	0.07	0.09	0.02	−0.01	0.02	0.11	0.01	0.04	−0.03	0.08	1			
13. Number of founders	1.33	0.58	−0.13	0	−0.09	−0.01	−0.1	−0.01	0.22	0.04	−0.06	−0.01	−0.08	−0.08	1		
14. Founder science professor	0.17	1.21	−0.03	0.02	0.04	−0.03	−0.12	−0.05	−0.04	0.08	−0.03	0.07	−0.06	0	−0.03	1	
15. Founder industry experience	0.71	0.46	−0.04	−0.05	−0.04	−0.02	−0.15	0.01	−0.15	0.06	−0.03	0.05	−0.02	−0.09	0.08	0.07	1
16. Founder management experience	0.56	0.52	−0.05	−0.04	−0.02	−0.03	−0.19	−0.01	−0.03	0	−0.03	0.06	−0.09	−0.11	0.28	0.1	0.45
17. Founder entrepreneurship experience	0.45	0.5	0	−0.05	0.08	0.03	−0.18	0.15	0.1	−0.23	−0.02	0.03	0.02	−0.03	0.02	0.12	0.22
18. Founder MD	0.32	0.47	−0.02	0.05	0.02	0.08	0.08	−0.06	0.15	0.09	0.04	−0.11	0.1	0	0.22	−0.08	−0.33
19. Founder Ph.D.	0.26	0.44	0.09	0.05	0.02	−0.01	−0.01	0.06	0.01	0.11	0.01	0	−0.08	−0.01	0.09	0.21	−0.13
20. Founder MBA	0.16	0.37	−0.04	−0.01	0.01	0.02	0.08	−0.13	0.02	0.1	−0.01	−0.03	0	−0.02	0.18	−0.06	−0.15
21. Founder JD	0.02	0.14	0	−0.01	0.06	−0.02	−0.01	0.23	−0.04	0.12	0.01	−0.03	−0.06	0.01	−0.03	−0.02	0.09
22. Founder non-star tech distance	0.33	0.2	−0.02	0.2	0.04	0	0.4	−0.1	0.23	0.02	−0.01	0.04	−0.02	0.04	−0.14	0.04	−0.09
23. Team size	3.07	5.35	0.12	0.27	0.44	0.22	0.07	0.1	0.06	0.25	−0.03	0.09	0.08	0.11	−0.05	−0.04	−0.04
24. Team clustering coefficient	0.2	0.31	0.2	0.42	0.56	0.27	−0.02	0.09	0.11	−0.13	0.05	0.05	0.19	0.15	−0.09	0.01	−0.1
25. Team density	0.16	0.3	0.05	0.2	0.24	0.16	−0.01	0.05	0.12	0.02	−0.05	0.08	0.08	0.12	−0.02	0.07	−0.03
26. Patent count	1.95	4.24	0.12	0.28	0.45	0.18	0.08	0.13	0.05	−0.27	−0.01	0.02	0.09	0.07	−0.06	−0.03	−0.03

(Continues)

TABLE 1 (Continued)

	16	17	18	19	20	21	22	23	24	25
16. Founder management experience	1									
17. Founder entrepreneurship experience	0.35	1								
18. Founder MD	−0.2	−0	1							
19. Founder PhD	−0.14	−0.1	−0.1	1						
20. Founder MBA	0.11	0.03	0.07	−0.13	1					
21. Founder JD	0.12	0.16	−0.1	−0.08	0.01	1				
22. Founder non-star tech distance	−0.03	0.01	−0.02	0.01	0.06	−0.02	1			
23. Team size	−0.03	0.01	0.09	−0.06	0.16	0.22	0.01	1		
24. Team clustering coefficient	−0.1	−0.1	0.03	−0.01	0.03	−0.01	0.03	0.58	1	
25. Team density	−0.06	−0	0.03	0.06	−0.05	−0.04	0.06	0.24	0.51	1
26. Patent count	−0.03	0.01	0.05	−0.05	0.09	0.3	0.03	0.82	0.49	0.16

[a]Correlations equal to or greater than 0.20 are significant at the 0.05 level.

TABLE 2 First-stage selection model for the likelihood of hiring stars

	Star hiring
S&P500	−7.764*
	(3.506)
Total funding	0.031***
	(0.007)
Founder science professor	0.101**
	(0.033)
Founder industry experience	−0.147
	(0.108)
Founder management experience	0.060
	(0.096)
Founder entrepreneurship experience	0.409***
	(0.092)
Founder MD	−0.051
	(0.096)
Founder Ph.D.	0.154
	(0.098)
Founder MBA	0.145
	(0.109)
Founder JD	0.862**
	(0.269)
Number of founders	1.173**
	(0.405)
Number of founders squared	−0.406***
	(0.111)
Constant	52.654*
	(25.063)
Year dummies	Yes
Location dummies	Yes
Wald $\chi 2$	261.94***
Number of firms	132

Note: Robust standard errors in parentheses.
***p < .001, **p < .01, *p < .05, +p < .1.

Table 3 presents the regression results for our hypothesis tests. For a conservative test of the study's hypotheses, we interpret all our results with two-tailed *t*-tests and estimate robust standard errors. Model 1 presents the regression results with all control variables incorporated. Model 1 shows that, consistent with previous literature, firm age is positively associated with new venture product introductions. We also find that the venture's level of financial resources is positively associated with new product introductions. We find support for our baseline prediction that star inventors and founder-inventors enable firms to launch more products, reflected in the positive, significant coefficients for these variables in Model 1. The year of star entry is negatively associated with new product introductions indicating that the year that stars join organizations is likely to be marked with significant disruption of existing organizational structures and greater team clustering is positively associated with new product

TABLE 3 Arellano–Bond GMM estimations of new product introductions by MIS ventures

	Model 1	Model 2	Model 3	Model 4	Model 5
Product introductions t−1	0.401***	0.425***	0.414***	0.418***	0.408***
	(0.055)	(0.059)	(0.057)	(0.058)	(0.058)
Star inventor	0.568***	0.494*	0.548**	0.518**	0.561**
	(0.171)	(0.196)	(0.198)	(0.196)	(0.198)
Founder-inventor	0.343*	0.365+	0.430*	0.315	0.387+
	(0.170)	(0.187)	(0.200)	(0.192)	(0.210)
Proportion of founder-star coinvention			−0.742*		−0.698*
			(0.311)		(0.304)
Founder-star tech distance				1.647*	1.514*
				(0.772)	(0.757)
Founder-star tech distance squared				−2.150*	−1.973*
				(1.002)	(0.981)
Star origin	−0.173	−0.008	0.042	−0.041	0.003
	(0.199)	(0.162)	(0.164)	(0.184)	(0.188)
Founder-star common employer	0.119	0.135	0.176	0.077	0.121
	(0.308)	(0.335)	(0.335)	(0.345)	(0.348)
Star entry	−1.194***	−1.228***	−1.099***	−1.258***	−1.133***
	(0.285)	(0.304)	(0.296)	(0.305)	(0.296)
Firm age	0.061**	0.035+	0.038+	0.043+	0.044+
	(0.021)	(0.020)	(0.020)	(0.024)	(0.024)
VC status	0.115	0.162	0.136	0.149	0.117
	(0.192)	(0.196)	(0.198)	(0.201)	(0.204)
Total funding	0.027**	0.025**	0.024**	0.025**	0.024**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Founder-inventor count	−0.001	−0.025	−0.007	−0.008	0.002
	(0.101)	(0.108)	(0.111)	(0.116)	(0.118)
Number of founders	−0.177	−0.030	−0.018	−0.047	−0.033
	(0.181)	(0.151)	(0.152)	(0.161)	(0.162)
Founder non-star tech distance	−0.818	−0.300	−0.242	−0.010	−0.113
	(0.588)	(0.572)	(0.540)	(0.535)	(0.555)
Team size	−0.010	−0.008	−0.006	−0.015	−0.013
	(0.015)	(0.012)	(0.012)	(0.013)	(0.012)
Patent count	−0.008	−0.012	−0.014	−0.011	−0.013
	(0.015)	(0.017)	(0.017)	(0.017)	(0.017)
Team clustering coefficient	0.608**	0.358+	0.379*	0.402*	0.425*
	(0.225)	(0.192)	(0.192)	(0.203)	(0.203)
Team density	−0.073	−0.128	−0.113	−0.124	−0.108
	(0.143)	(0.155)	(0.156)	(0.154)	(0.155)
Inverse Mills ratio		1.267+	1.275+	1.377*	1.342*
		(0.671)	(0.654)	(0.691)	(0.673)

TABLE 3 (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	−0.114	−0.772	−0.757	−0.831	−0.886
	(0.599)	(0.634)	(0.682)	(0.704)	(0.699)
Observations	1,158	1,158	1,158	1,158	1,158
Year dummies	Yes	Yes	Yes	Yes	Yes
Location dummies	Yes	Yes	Yes	Yes	Yes
Industry subsegment dummies	Yes	Yes	Yes	Yes	Yes
Number of firms	132	132	132	132	132
Wald $\chi 2$	1,733.74***	1,103.35***	839.14***	706.88***	801.15***
AR(1)	−3.22**	−4.38**	−4.45**	−4.31**	−4.46**
AR(2)	1.32	0.76	0.82	0.77	0.82
Hansen J test	80.72	85.79	80.82	73.22	73.93

Note: Model specification—Arellano–Bond GMM estimations at time t; Robust standard errors in parentheses ();
***$p < .001$, **$p < .01$, *$p < .05$, + $p < .1$, two-tailed t-tests.

introductions. In addition, the coefficient of the lagged dependent variable is positive and statistically significant ($p < .01$) for all models. This supports our expectation underlying the GMM model that prior levels of product performance influence firm product performance for subsequent years.

In Model 2 (Table 3), we add the Inverse Mills ratio corresponding to the selection effect of stars into the new venture. The Inverse Mills ratio is marginally significant ($p < .1$) indicating that there is some evidence of endogeneity due to selection effects. In Model 3 (Table 3), we add the variable corresponding to Hypothesis 1—the proportion of founder-star coinvention. Hypothesis 1 predicted that the firms that have a greater proportion of their innovation activities being performed jointly by stars and founder-inventors are likely to suffer a negative effect on innovation, as opposed to a beneficial effect when they are active separately. We test this in Model 3 (Table 3) through the proportion of patents coinvented by stars and founders, calculated based on the firm's annual patenting activity, while controlling for the direct effects of each individually. We find that the proportion term is negative and significant (Model 2, $\beta = -0.742$, $p < .05$).

Hypothesis 2 posits that there is a curvilinear, inverted U-shaped relationship between the degree of similarity of the founder-inventor and star inventor's technological knowledge domains and the new venture's number of product introductions. To test this hypothesis, we add the variables corresponding to founder-star technological distance to the model, Model 4 (Table 3). In Model 4, the coefficient of the linear term for founder-star technological distance is positive and significant ($\beta = 1.647$, $p < .05$) while the squared term is negative and significant ($\beta = -2.15$, $p < .05$). This supports Hypothesis 2. We now add the variables corresponding to the proportion of founder-star coinvention and founder-star technological distance to obtain our full model in Model 5 (Table 3). We can estimate the "inflection point" of the curve by calculating the partial derivative:

$$\frac{\partial ProductIntroductions_i}{\partial founder-star\ tech\ distance_i} = \beta_1 + 2\beta_2\ founder-star\ tech\ distance_i$$

Using the value of the coefficients from Model 3 (Table 3), we calculate the inflection point to be 0.38. This indicates that the relationship between founder-star technological distance and product launch is increasingly positive until the founder-star tech distance reaches the 0.38 threshold. Beyond this point, increases in founder-star technological distance have a detrimental impact on the launch of new products. Figure 2 offers a graphical representation of the relationship between the founder-star technological distance and number of product introductions of the new venture. Values closer to zero illustrate firms where founder(s) and star(s) leverage more similar knowledge domains while values that are closer to one represent firms where founder(s) and star(s) exhibit more disparate knowledge, with the results indicating an optimal founder-star tech distance of ~0.4.

Our results reinforce the economic importance of the effects we study. A one standard deviation increase in the proportion of founder and star coinvention is associated with a 9% decrease in the number of product introductions in a given year. With respect to founder-star technological distance, a one standard deviation increase (beyond the optimal level) leads to a 17% decrease in the number of product introductions.

4.1 | Post-hoc analysis

We conducted a post-hoc analysis to examine whether the results we observe were due to informal hierarchy or alternative explanations. To do so, we examined differences in the type of prior work experience among star scientists in our data. Based on our theoretical logic, stars who were most recently employed by older organizations (e.g., Becton, Dickinson and Company, Medtronics, Abbott Labs and SRI international, in our data) are likely to be significantly more disruptive in a new venture setting as opposed to stars most recently employed by younger organizations. This is because star inventors previously employed by older organizations are more likely to be accustomed to norms and expectations of formal organizational hierarchy that start-ups are less likely to have (Freeman, 1986; Sørensen, 2007).

We tested this premise by interacting the binary variable *star origin* (that was set to one if the firm had at least one star who was most recently employed by an older organization) with the variable *proportion of founder-star coinvention*. The resulting interaction term was negative and significant (Model 1, Table 4). Figure 3 plots this interaction. As hypothesized, we find that the negative effect of founder-star coinvention is significantly higher if the star inventor was previously employed by an older established organization. This supports our theoretical argument that the negative effect of founder-star coinvention is driven by conflict arising from informal hierarchy as opposed to alternate explanations.

We also considered an additional outcome that was consistent with our theoretical model.[5] Specifically, we considered the impact of the knowledge generated by the firm in the form of external forward patent citations. We coded the *impact* dependent variable by considering the number of 5-year external forward citations generated by the patents of the focal firm in a specific year. This measure has often been used in prior research to reflect the quality or overall impact of developed knowledge (e.g., Basu et al., 2015). The results of this analysis are tabulated in

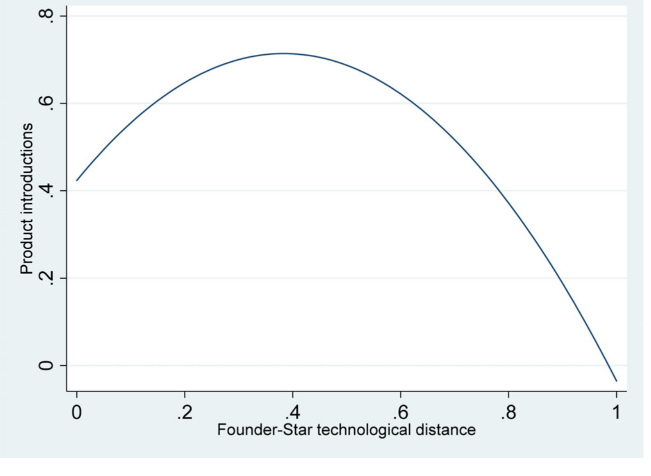

FIGURE 2 Graphical representation of H2

TABLE 4 Post-hoc analysis

	Model 1 (product introductions)	Model 2 (knowledge impact)
Product introductions $_{t-1}$	0.405***	
	(0.066)	
Star inventor	0.489*	1.341***
	(0.197)	(0.223)
Founder-inventor	0.285	2.155***
	(0.224)	(0.202)
Proportion of founder-star coinvention	−1.128*	−1.765*
	(0.479)	(0.887)
Founder-star tech distance	2.282**	4.907***
	(0.885)	(0.965)
Founder-star tech distance squared	−2.618*	−6.567***
	(1.164)	(1.250)
Star origin	0.171	−0.529
	(0.198)	(0.234)
Star origin * proportion of founder-star coinvention	−1.113*	
	(0.556)	
Founder-star common employer	0.060	−0.781*
	(0.327)	(0.316)
Star entry	−1.193***	0.262
	(0.331)	(0.270)
Firm age	0.052+	−0.081**
	(0.029)	(0.031)
VC status	0.072	0.107
	(0.200)	(0.228)
Total funding	0.028**	0.060***
	(0.010)	(0.016)
Founder-inventor count	0.093	−0.509***
	(0.105)	(0.105)
Number of founders	−0.124	−0.074
	(0.166)	(0.189)
Founder non-star tech distance	−0.754	−0.114
	(0.493)	(0.514)
Team size	−0.001	−0.011
	(0.012)	(0.017)
Patent count	−0.017	0.004
	(0.015)	(0.019)
Team clustering coefficient	0.049	0.860*
	(0.272)	(0.350)

(Continues)

TABLE 4 (Continued)

	Model 1 (product introductions)	Model 2 (knowledge impact)
Team density	−0.138	0.082
	(0.141)	(0.330)
Inverse mills ratio	0.516	−0.367
	(0.669)	(0.711)
Constant	−0.214	−16.325***
	(0.668)	(0.836)
Observations	1,158	1,158
Year dummies	Yes	Yes
Location dummies	Yes	Yes
Industry subsegment dummies	Yes	Yes
Number of firms	132	132
Wald $\chi 2$	971.04***	719.34***
Pseudo R^2		0.2261
AR(1)	−4.65***	
AR(2)	0.81	
Hansen J test	75.10	

Note: Model specification for Model 1—Arellano–Bond GMM estimations at time t; Robust standard errors in parentheses (). Model 1 incorporates an interaction between proportion of founder-star coinvention and star origin. Model specification for Model 2—Negative Binomial; Robust standard errors in parentheses (); Model 2 incorporates knowledge impact as the dependent variable. ****p* < .001, ***p* < .01, **p* < .05, +*p* < .1, two-tailed *t*-tests.

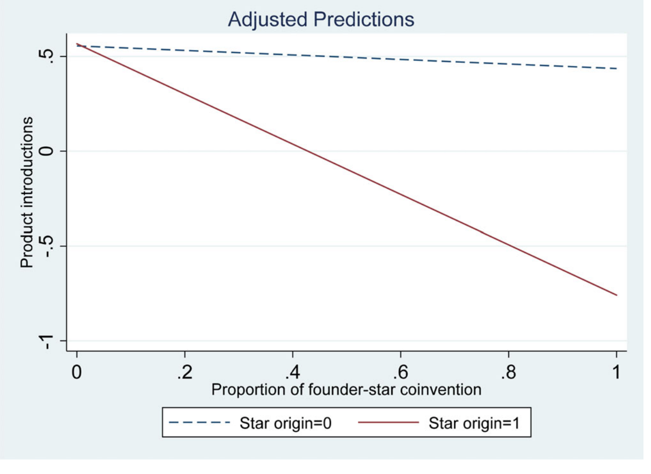

FIGURE 3 Post-hoc analysis: Interaction of proportion of founder-star coinvention and star origin

Table 4 (Model 2). Similar to our results with product introductions, we find that although star inventors and founder-inventors are individually positively associated with knowledge impact, the proportion of founder-star coinvention is negatively associated with knowledge impact. This offers additional support for our theoretical framework suggesting that collaboration between stars and founder-inventors has a dysfunctional effect on the innovation team.

4.2 | Additional analyses

We conducted several robustness checks to assess and verify the strength of our findings. First, we reran our analysis with the full sample of firms for which we had founder data, including those that had no record of patenting during the period of the study. This provided more conservative tests for our hypotheses as it involved the inclusion of many firms for which our key independent variables were set to zero. When running this test, we separately controlled for heterogeneity among firms with respect to their patenting records by incorporating a binary variable (*firm patenting dummy*) that was set to one if the firm had any patent on record during the observation period and zero, if not. The results supported both of our hypotheses and are summarized in Model 1 (Table 5).

We also examined the direct interaction of the founder-inventor and star inventor variables to see if this specification supported our theorizing that this type of coinvention would impair product introductions. The interaction term is negative and significant, supporting Hypothesis 1. The results are summarized in Model 2 (Table 5).

Another possibility we probed relates to the interaction between the proportion of founder-star coinvention and founder-star technological distance. In hypothesis 1, we argued that there is a negative relationship between the proportion of founder-star coinvention and the venture's number of product introductions. In hypothesis 2, we predict a curvilinear relationship between founder-star technological distance and the number of product introductions. Theoretically, there could be an interactive effect between proportion of founder-star coinvention and founder-star technological distance. When founder-star technological distance is high, a greater proportion of founder-star coinvention is likely to strengthen their mutual capacity to understand and leverage shared knowledge. The effect of this on clarifying innovation leadership is unclear. However, we might expect that higher proportion of founder-star coinvention may improve firm performance when founder-star technological distance is high. When founder-star technological distance is low, a greater proportion of founder-star coinvention may exacerbate ambiguity in social hierarchy and innovation leadership in the firm while not significantly increasing the founder-inventor and star's mutual capacity to understand and leverage each other's knowledge toward furthering the firm's innovation goals. In this case, we would expect that greater proportion of founder-star coinvention is likely to be particularly detrimental for firm performance when founder-star technological distance is low. We probed these ideas by interacting the variables proportion of founder-star coinvention and the founder-star distance relationship. However, the interaction was not significant (p-value = .14).[6]

We also considered the possibility that there might be some differential effect of having more than one star performer in the innovation team of the firm. To investigate this further, we broke down our stars variable into single and multi-star firms. For firms with single stars, we created a variable *Single Star* that was the proportion of annual founder and star patents, calculated based on the total number of annual firm patents. For firms with more than one star, we created a separate variable *Multiple Star*, which calculated a similar proportion of annual founder and stars' patents to the firm's annual patents. We then test our hypotheses again by incorporating these two variables as a substitute for our original founder-star coinvention variable (*proportion of founder-star coinvention*). We found our results to hold for both single star and multiple star firms (Table 5, Model 4, β (Single Star) = -1.149, $p < .05$; β (Multi Star) = -0.680, $p < .05$). This result provides additional evidence that our finding pertaining to the negative interactive effect of stars and founder collaboration on product introduction is not driven by a differential effect of having more than one star performer in the innovation team of the firm.

Another alternative explanation that we probed is whether potential redundancy and resource inefficiency of having both founder-inventors and star scientists may explain our findings. Startup firms such as those sampled in our study are likely to face significant resource constraints, suggesting that inefficiencies in R&D or other activities could significantly undermine their success. We conducted a robustness test for this potential effect by including an interaction term between number of founders and founder-inventor. If the founding team's distraction from other duties accounts for negative effects on product launch, this problem should be exacerbated for smaller founding teams. However, our results suggest that this is not the case, as the interaction term remained insignificant. At the same time, the hypothesized effects also remain significant, consistent with our theoretical framework.

TABLE 5 Robustness checks

	Model 1	Model 2	Model 3	Model 4	Model 5
Product introductions$_{t-1}$	0.430***	0.408***	0.401***		0.436***
	(0.056)	(0.057)	(0.060)		(0.046)
Product introductions$_{t-1}$ (logged)				0.401***	
				(0.064)	
Star inventor	0.500*	0.876***	0.551**	0.132*	0.613**
	(0.212)	(0.250)	(0.202)	(0.064)	(0.204)
Founder-inventor	0.441+	0.703**	0.446*	0.066	0.522**
	(0.229)	(0.231)	(0.223)	(0.073)	(0.176)
Founder-inventor * star inventor		−0.847**			
		(0.315)			
Proportion of founder-star coinvention	−0.671*			−0.176*	−0.927**
	(0.306)			(0.079)	(0.323)
Proportion of founder-star coinvention (single star)			−1.149*		
			(0.556)		
Proportion of founder-star coinvention (multi star)			−0.680*		
			(0.317)		
Founder-star tech distance	1.605*	1.580*	1.655*	0.728**	1.764**
	(0.748)	(0.688)	(0.810)	(0.238)	(0.649)
Founder-star tech distance squared	−2.092*	−1.967*	−2.157*	−1.020**	−2.303**
	(1.015)	(0.897)	(1.074)	(0.328)	(0.825)
Star origin	−0.060	0.054	0.017	−0.006	−0.121
	(0.215)	(0.178)	(0.208)	(0.071)	(0.207)
Founder-star common employer	0.166	0.083	0.127	0.005	−0.012
	(0.375)	(0.344)	(0.359)	(0.114)	(0.283)
Star entry	−1.233***	−1.190***	−1.120***	−0.274**	−0.928**
	(0.334)	(0.297)	(0.304)	(0.093)	(0.347)
Firm age	0.051+	0.055**	0.056*	0.016*	0.030
	(0.026)	(0.021)	(0.028)	(0.008)	(0.021)
VC status	0.094	0.164	0.117	0.056	0.159
	(0.198)	(0.193)	(0.210)	(0.064)	(0.259)
Total funding	0.029***	0.023**	0.029***	0.007*	0.021*
	(0.009)	(0.008)	(0.009)	(0.003)	(0.009)
Founder-inventor count	−0.001	0.048	0.006	0.023	−0.028
	(0.133)	(0.117)	(0.127)	(0.040)	(0.124)
Number of founders	−0.132	−0.021	−0.067	−0.015	−0.053
	(0.192)	(0.148)	(0.180)	(0.048)	(0.174)
Founder non-star tech distance	−0.573	−0.084	−0.326	−0.017	−0.528
	(0.615)	(0.510)	(0.625)	(0.164)	(0.573)

TABLE 5 (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5
Team size	−0.014	−0.015	−0.015	−0.006	−0.022+
	(0.012)	(0.012)	(0.011)	(0.004)	(0.012)
Patent count	−0.008	−0.009	−0.010	−0.002	−0.000
	(0.016)	(0.017)	(0.016)	(0.005)	(0.020)
Team clustering coefficient	0.699**	0.453*	0.488*	0.087	0.237
	(0.228)	(0.206)	(0.216)	(0.068)	(0.177)
Team density	−0.093	−0.100	−0.116	−0.037	−0.161
	(0.148)	(0.157)	(0.156)	(0.048)	(0.171)
Inverse Mills ratio	1.004	1.456*	1.310+	0.474*	0.823
	(0.729)	(0.693)	(0.695)	(0.230)	(0.558)
Firm patenting dummy	0.355				
	(0.418)				
Constant	−0.655	−1.113	−0.982	−0.300	−0.128
	(0.788)	(0.734)	(0.744)	(0.237)	(0.605)
Observations	1,323	1,158	1,158	1,158	725
Year dummies	Yes	Yes	Yes	Yes	Yes
Location dummies	Yes	Yes	Yes	Yes	Yes
Industry subsegment dummies	Yes	Yes	Yes	Yes	Yes
Number of firms	161	132	132	132	84
Wald $\chi 2$	1072***	701.35***	673.18***	490.27***	4,615.03***
AR(1)	−4.44**	−4.31**	−4.46**	−5.03**	−3.51**
AR(2)	1.10	0.71	0.73	0.10	1.02
Hansen J test	103.02	70.06	70.83	76.93	18.70

Note: Model specification—Arellano–Bond GMM estimations at time t; Robust standard errors in parentheses (). Model 1 includes firms with no patenting history; Model 2 incorporates an interaction term instead of the variable, proportion of founder-star coinvention; Model 3 breaks up the variable, proportion of founder-star coinvention, for single stars and multiple stars, Model 4 incorporates a logged dependent variable and Model 5 excludes acquired firms. ***$p < .001$, **$p < .01$, *$p < .05$, +$p < .1$, two-tailed *t*-tests.

We also considered the possibility that our results could be driven by firms that are ultimately acquired, since the presence of a star inventor at the venture may make it an appealing acquisition target. In such cases, product introductions by the venture may not be observed because it is acquired before they occur. To probe this potential explanation, we reran our analysis but excluded all firms that were ultimately acquired in our sample. This limited our sample to 84 firms. Our results continued to hold in this smaller subset of firms and are reported in Model 5 (Table 5).

In additional, unreported analyses (available from the authors on request), we reran our models with alternate specifications. Since our dependent variable is the number of product introductions by the firm in a year, statistical models for count data such as the Poisson or Negative Binomial are the most appropriate. The distribution of our data on product introductions indicated over dispersion, making the negative binomial distribution a preferred choice. Of the 132 firms in our sample, 46 introduce no products across the years of observation. Standard negative binomial models cannot handle the presence of zero counts of the dependent variable which may be a result of unobserved firm heterogeneity (Blundell, Griffith, & Van Reenen, 1995). To address this problem of excess zeros in the data, the zero-inflated negative binomial model (ZINB) is the preferred estimation technique. We used the total amount of funding received by the venture (*total funding*) and the total size of the innovation team (*team size*) as parameters for predicting zero new venture product introductions in the zero-inflation model. We followed the recommendation offered by Greene (2003) and applied the Vuong test statistic (Vuong, 1989) to confirm that the zero-inflated model was a better fit compared to the standard negative binomial model for our data. This specification also afforded robust support for both our hypotheses.

In order to test whether our results are robust to arbitrary patterns of serial autocorrelation that may underlie the panel nature of our data set, we used Poisson quasi-maximum likelihood (QML) estimation to obtain a more conservative estimate of the coefficients (Wooldridge, 2002). A key advantage of this method is that as long as the mean of the dependent variable is correctly specified, the coefficient estimates are consistent and the robust standard errors thus generated remain consistent even if the underlying data-generating process is not Poisson (Gourieroux, Monfort, & Trognon, 1984). Although the time invariant nature of many of our key independent variables means that we are unable to test both of the hypotheses using this modeling technique, we are able to test the negative interactive effect of founder-inventors and star inventors based on the time varying proportion of founder-star collaboration. The imposition of QML led to several firms in our sample that had largely time invariant variables dropping out, and we were left with a sample size of 79 firms with this test. Despite the smaller sample, which significantly reduced the power of the test, we found that the coefficient of the proportion of founder-star coinvention was partially significant (p = .08).

It is possible that the influence of inventors will decline over longer periods, reducing their impact on the commercialization of technologies. To test this, we reran our analysis using 3-year and 5-year moving averages. For all of these analyses, our results were substantively the same as the results reported for our primary analysis. We also ran our models by lagging all patent-based variables, which are time variant by 2 years, and our results stayed consistent. In addition, we ran our models by taking 3- and 2-year moving windows for patent-based variables and our main results stay significant. Finally, we incorporated lags of 2 and 3 years as instruments in our model (since xtabond uses lags of variables as instruments) and our results again held up. Log-linear models can help to avoid the problem of "Simpson's Paradox," wherein a pair of variables can spuriously have a relationship opposite in direction to their actual relationship (Christensen, 2006). Hence, we also ran our analysis by logging our dependent variable and have reported the results in Model 4 (Table 5). Both our hypotheses continue to hold. Finally, we calculated variance inflation factors (VIF) for the full model. Typically, VIF values less than five indicate that multicollinearity is not a concern in the regression model (Chatterjee, Hadi, & Price, 2000; Kennedy, 2008). We verified that all our models satisfied this condition (mean VIF was 1.58 with a maximum VIF value of 3.61), suggesting that multicollinearity is not a serious problem in our analysis.

5 | DISCUSSION

Researchers have long sought to understand how the organizational design of new ventures and founders' early choices in constructing this enables the venture to pursue promising commercial applications. Having highly accomplished individuals or "stars" on the innovation team has been shown to be an important means of achieving significant performance gains for firms (Hess & Rothaermel, 2011; Kehoe & Tzabbar, 2015; Toole & Czarnitzki, 2009; Zucker et al., 2002). However, while scholars have made important strides in understanding the value of star performers as individual contributors, little work has examined the fit between star performers and the organizations in which they work (Call, Nyberg, & Thatcher, 2015). Founders of new ventures face especially critical choices around the organization and makeup of the innovation team that have important consequences for the venture's future success. Our research points to the hazards of fostering close collaboration between individuals who draw their standing from different sources of social hierarchy, focusing particular attention on the potentially precarious combination of talented star inventors and firm founders. In doing so, we offer important insights into the relationship between organizational design and new venture outcomes.

A new venture's innovation team is central to its success, and critical decisions about the composition of the team must be made early on. While the recruitment of star inventors offers an attractive option to new ventures seeking to commercialize new technologies, our empirical results show that firms need to exercise caution in hiring as well as managing star employees. Although our results are consistent with other studies on star scientists that have found a positive result of stars on firms' innovation success (e.g., Higgins, Stephan, & Thursby, 2011; Zucker et al., 1998), our results also point to boundary conditions around the benefits that star performers can provide for innovation. In highlighting the problems of egalitarianism versus hierarchy in new ventures, Wasserman (2012) noted that as ventures evolve over time, they typically have to adopt a more hierarchical structure, which can be a difficult process, but failure to do so, "can be even more painful" (p.124). In our study, we demonstrate that founder-inventors, whose standing within the informal hierarchy of the innovation team derives mainly from their heirarchical position, may come into conflict with star inventors, who derive their hierarchical standing from past innovation success. This appears to result in a strong negative effect on product introduction. Our findings lead us to suggest that founders who hire star inventors should not only establish a clear hierarchy in decision-making within the innovation teams, but also potentially offer greater autonomy to the star inventor in matters concerning innovation leadership and product development, even if the founder is technologically proficient. We also suggest that it may be advantageous for founders to hire star inventors with prior experience in working in new ventures as opposed to older established organizations. Our findings align with prior work that has shown that firms may experience suboptimal results when they organize their innovation teams such that experienced inventors have to work under managerial supervision and guidance (Conti et al., 2014) or when the presence of stars fosters an over-reliance on their contributions resulting in inhibiting non-star teammates' knowledge acquisition (Li, Li, Li, & Li, in-press).

Another key decision that ventures face when configuring their innovation teams is whether to recruit team members of similar or different technological backgrounds. Past research has found support for both approaches, and our results reveal that a balance should be struck between them. The degree of similarity between the founder's and star inventor's technological knowledge domains has an inverted U-shaped effect on product introductions by the venture, a finding that is consistent and robust across all of our models and post-hoc tests. This finding is consistent with prior research in other contexts that has underscored the need to balance the extent of knowledge overlap between key subgroups involved in knowledge creation in new ventures (e.g., Basu et al., 2015).

Our study contributes to the literature on stars, venture team composition, and the internal design of innovative efforts in the new venture. As Bercovitz and Feldman (2011) note, much remains to be understood about why some innovation teams successfully create new products and others do not. Research on both star scientists and founder-inventors have independently argued for the benefits of incorporating each of these types of individuals in the innovation team (Bercovitz & Feldman, 2008; Toole & Czarnitzki, 2009). However, an emerging body of evidence suggests that there are also significant challenges in managing highly productive individuals within organizations. Having stars within the firm may lead to an excessive amount of organizational resources to be garnered by the star which can hinder capability development of non-stars (Kehoe & Tzabbar, 2015) or may lead to the development of suboptimal task structures within the organization (Chen & Garg, 2018). Too many stars within the organization can lead to jockeying for power and diminish firm performance (Groysberg et al., 2011). Our study extends this literature by suggesting that organizational dysfunction may also occur when a star inventor and a founder-inventor work together on the same innovation team, as each of them draw their standing from different sources. Our study also extends recent research on group interactions by showing that highly accomplished team members may have difficulty working together, undermining their ability to collaborate (Groysberg et al., 2011). More broadly, our results extend the recent work of Sauermann and Cohen (2010) and Joshi and Knight (2015), to further understand how individual expertise and inherent hierarchical structures act together to promote or limit the efforts of innovative and scientific teams. In sum, our research adds further insight to prior work, demonstrating that organizations must carefully consider the composition of innovation teams to maximize the value added by stars.

The limitations of our study suggest promising opportunities for future research. First, we rely on patent records to determine innovation team membership. Organizations are required by law to list all individuals who made substantial contributions to the conception and design of a given invention (Ducor, 2000).[7] Although patenting of medical devices is considered a critical part of firm strategy in this industry (Chatterji, 2009), patents represent an intermediate innovation output (Griliches, 1990). As such, a limitation of relying on patent data are those not every product may be patented and not every patent underlies a novel process or product introduced by the firm. As a result, we do not capture the influence of any participant in the innovation team not listed on a patent, despite the possibility that otherwise influential collaborators may not have been directly engaged in patenting activities (a possibility that we note is unlikely, based on our informants' explanations of industry and firm practices). Future research based on employment records or other data sources may provide an improved understanding of the dynamics of innovation teams. Second, in the industry we study, patents may play a more important role in the innovation process than in other industries. However, one strength of our study design lies in our use of new product introductions as an outcome variable; new product introductions are likely to be considered an important outcome across all technology and manufacturing industries. Thus, to the extent that our patent-based covariates provide a reasonably accurate depiction of the characteristics of a new venture's innovation team, we believe that the observed effects of these characteristics are generalizable to a broader universe of industries. Third, our study does not account for the alternative explanation that the negative interaction between stars and founder-inventors we observe could be a result of constraints on inventors' time when they are on same team thereby limiting independent efforts. Finally, we note that the medical device industry in the US likely differs from that observed in other countries. Ventures in our setting face similar regulatory and resource environments, however these could be materially different from that faced in other institutional environments. Future scholarship may consider how differing institutional environments may affect the impact of team composition on innovation outcomes.

Future research may reveal further insights into clashes between team members who derive their standing from different sources. As Joshi and Knight (2015) highlighted, there are multiple dynamics at play when teams collaborate. Although our research is focused specifically on standing based on either expertise or hierarchical position, our theory suggests that any divergent sources of high status may yield similarly dysfunctional results. For example, the presence of individuals whose status is based on important external affiliations or connection to socially prominent institutions may also produce conflict within teams. Alternately, conflict may be particularly intense when stars and founders are different in terms of gender or ethnicity (cf., Jung, Vissa, & Pich, 2017). Given the wide range of possible sources of status and standing, it would be interesting to compare the impact of different combinations of types of high-status individuals and examine whether there are combinations that are particularly disruptive. Furthermore, our study focuses on new product introductions, and future research could examine whether products delayed by these potential clashes also suffer in terms of outcomes such as sales, market share, or return on investment. Results from such research could also indicate whether teams suffering clashes among prominent individuals may ultimately deliver better products, in some way justifying the challenges experienced during the development process. Our findings may also open fruitful new avenues for research concerning other types of potential conflict between star inventors and management. As such, conflicts may result in the departure of a star inventor or turnover in the top management team, it would be beneficial to determine the conditions under which these detrimental outcomes are most likely.

Our research directs attention to the composition of the innovation team as a key mechanism for understanding the introduction of new technologies and the performance of technology-based new ventures. By simultaneously capturing the beneficial influence of a moderate degree of technical similarity between innovators and the detrimental effects of conflicts among accomplished team members, our study contributes to active streams of research in the fields of knowledge creation and entrepreneurship. Future research in this area holds the promise of helping to gain greater insight into how founders of entrepreneurial ventures may best design their organizations, assembling teams to launch successful innovations.

ACKNOWLEDGEMENTS

We are indebted to thoughtful comments of our editor, Dr. Diane Burton, and to three anonymous reviewers who helped us refine this manuscript. We are grateful to participants at seminars and conferences where we presented this research for their insights and help in shaping earlier versions of this paper. We are especially thankful to Dr. Sudipta Sinha for his assistance with writing the program that was used to disambiguate the founder data. This project was partially funded with a Kauffman Dissertation Grant (for the second Author) and by the Arthur W. Buerk Center for Entrepreneurship at the University of Washington. We also appreciate the support of the McFerrin Center for Entrepreneurship in the Mays Business School, Texas A&M University.

ENDNOTES

[1] We consider the innovation team to represent the set of individuals in the venture with technological expertise who participate in the development and commercialization of the new venture's products.

[2] For example, one firm in our sample had four patents with application dates in the year 2000, and of these three were jointly authored between the founder and the star inventor. In this case, the proportion of founder-star coinvention has a value 0.75 for the year 2000 for this firm. On the other hand, for another firm in our sample, the number of co-authored patents between the founder and star in the year 2000 was one of five patents filed by the firm in the year, leading to the value of 0.2 for the proportion of founder-star coinvention for this firm in the year 2000.

[3] An alternate operationalization of this variable was tested using average distance between the founder-star dyad. The results were consistent for both measures.

[4] Specifically, we calculated the technological distance between the founder's patents and those of the non-star inventors in the innovation team based on their patenting history in the 5-year period prior to the founding of the focal firm. The maximum of the distances thus calculated was used as the founder non-star technological distance.

[5] We would like to thank the editors of the special issue for encouraging us to investigate this.

[6] These results are available from the authors. We appreciate the suggestions of the editors and an anonymous reviewer to consider these effects.

[7] Specifically, the statute of US law states, “Inventors may apply for a patent jointly even though (a) they did not physically work together or at the same time, (b) each did not make the same type or amount of contribution, or (c) each did not make a contribution to the subject matter of every claim of the patent.”(35 U.S.C. §116).

ORCID

Amrita Lahiri https://orcid.org/0000-0002-4034-5885
Michael D. Howard https://orcid.org/0000-0001-5886-9233

REFERENCES

Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, *22*(3), 197–220.

Ancona, D. G., & Caldwell, D. F. (1992). Demography and design: Predictors of new product team performance. *Organization Science*, *3*(3), 321–341.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*(2), 277–297.

Audia, P. G., & Goncalo, J. A. (2007). Past success and creativity over time: A study of inventors in the hard disk drive industry. *Management Science*, *53*(1), 1–15.

Azoulay, P., Graff Zivin, J., & Wang, J. (2010). Superstar extinction. *Quarterly Journal of Economics*, *25*, 549–589.

Azoulay, P., Graff Zivin, J. S., & Manso, G. (2011). Incentives and creativity: Evidence from the academic life sciences. *The Rand Journal of Economics*, *42*(3), 527–554.

Baba, Y., Shichijo, N., & Sedita, S. R. (2009). How do collaborations with universities affect firms' innovative performance? The role of "Pasteur scientists" in the advanced materials field. *Research Policy*, *38*(5), 756–764.

Baron, J. N., Hannan, M. T., & Burton, M. D. (1999). Building the iron cage: Determinants of managerial intensity in the early years of organizations. *American Sociological Review*, *64*(4), 527–547.

Bascle, G. (2008). Controlling for endogeneity with instrumental variables in strategic management research. *Strategic Organization*, *6*(3), 285–327.

Basu, S., Sahaym, A., Howard, M. D., & Boeker, W. (2015). Parent inheritance, founder expertise, and venture strategy: Determinants of new venture knowledge impact. *Journal of Business Venturing*, *30*(2), 322–337.

Beckman, C. M., & Burton, M. D. (2008). Founding the future: Path dependence in the evolution of top management teams from founding to IPO. *Organization Science*, *19*(1), 3–24.

Beckman, C. M., Burton, M. D., & O'Reilly, C. (2007). Early teams: The impact of team demography on VC financing and going public. *Journal of Business Venturing*, *22*(2), 147–173.

Benjamin, B. A., & Podolny, J. M. (1999). Status, quality, and social order in the California wine industry. *Administrative Science Quarterly*, *44*(3), 563–589.

Berchicci, L. (2013). Towards an open R&D system: Internal R&D investment, external knowledge acquisition and innovative performance. *Research Policy*, *42*(1), 117–127.

Bercovitz, J., & Feldman, M. (2008). Academic entrepreneurs: Organizational change at the individual level. *Organization Science*, *19*(1), 69–89.

Bercovitz, J., & Feldman, M. (2011). The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. *Research Policy*, *40*(1), 81–93.

Berger, J., Cohen, B. P., & Zelditch, M., Jr. (1972). Status characteristics and social interaction. *American Sociological Review*, *37*(3), 241–255.

Berger, J., Ridgeway, C. L., Fisek, M. H., & Norman, R. Z. (1998). The legitimation and delegitimation of power and prestige orders. *American Sociological Review*, *63*(3), 379–405.

Blau, P. M. (1977). *Inequality and heterogeneity: A primitive theory of social structure*. New York: Free Press.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143.

Blundell, R., Griffith, R., & Van Reenen, J. (1995). Dynamic count data models of technological innovation. *The Economic Journal*, *105*, 333–344.

Bonacich, P. (1987). Power and centrality: A family of measures. *American Journal of Sociology*, *92*(5), 1170–1182.

Call, M. L., Nyberg, A. J., & Thatcher, S. (2015). Stargazing: An integrative conceptual review, theoretical reconciliation, and extension for star employee research. *Journal of Applied Psychology*, *100*(3), 623–640.

Certo, S. T. (2003). Influencing initial public offering investors with prestige: Signaling with board structures. *Academy of Management Review*, *28*(3), 432–446.

Chatterjee, S., Hadi, A. S., & Price, B. (2000). *Regression analysis by example*. New York: Wiley.

Chatterji, A. K. (2009). Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. *Strategic Management Journal*, *30*(2), 185–206.

Chen, J. S., & Garg, P. (2018). Dancing with the stars: Benefits of a star employee's temporary absence for organizational performance. *Strategic Management Journal*, *39*(5), 1239–1267.

Christensen, R. (2006). *Log-linear models and logistic regression*. New York, NY: Springer Science & Business Media.

Cohen, W., Nelson, R., & Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not) (NBER Working Paper No. 7552). Cambridge, MA: National Bureau of Economic Research.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152.

Colombo, M. G., & Grilli, L. (2013). The creation of a middle-management level by entrepreneurial ventures: Testing economic theories of organizational design. *Journal of Economics & Management Strategy*, *22*(2), 390–422.

Conti, R., Gambardella, A., & Mariani, M. (2014). Learning to be Edison: Inventors, organizations, and breakthrough inventions. *Organization Science*, *25*(3), 833–849.

Dahlander, L., & McFarland, D. A. (2013). Ties that last tie formation and persistence in research collaborations over time. *Administrative Science Quarterly*, *58*(1), 69–110.

Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of Economic Literature*, *26*(3), 1120–1171.

Ducor, P. (2000). Coauthorship and coinventorship. *Science*, *289*(5481), 873–875.

Edwards KL, Gordon TJ. 1984. *Characterization of Innovations Introduced on the US Market in 1982*. The Futures Group, U.S. Small Business Administration, Contract No. SBA-6050–0A-82.

Eesley, C. E., Hsu, D. H., & Roberts, E. B. (2014). The contingent effects of top management teams on venture performance: Aligning founding team composition with innovation strategy and commercialization environment. *Strategic Management Journal*, *35*(12), 1798–1817.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, *47*(1), 117–132.

Freeman, J. (1986). Entrepreneurs as organizational products: Semiconductor firms and venture capital firms. In G. Libecap (Ed.), *Advances in the study of entrepreneurship, innovation, and economic growth* (pp. 33–58). Greenwich, CT: JAI Press.

Gerber S. 2014. 11 conflicts between startup founders and employees. http://readwrite.com/2014/01/27/startup-founders-employees-conflicts [10-20-2015].

Gould, R. V. (2002). The origins of status hierarchies: A formal theory and empirical test. *American Journal of Sociology*, *107* (5), 1143–1178.

Gourieroux, C., Monfort, A., & Trognon, A. (1984). Pseudo maximum likelihood methods: Theory. *Econometrica: Journal of the Econometric Society*, *52*, 681–700.

Graham, S. J., Merges, R. P., Samuelson, P., & Sichelman, T. (2009). High technology entrepreneurs and the patent system: Results of the 2008 Berkeley patent survey. *Berkeley Technology Law Journal*, *24*, 1255.

Greene, W. H. (2003). *Econometric analysis*. New York: Prentice Hall.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, *28*(4), 1661–1707.

Groysberg, B., Lee, L.-E., & Nanda, A. (2008). Can they take it with them? The portability of star knowledge workers' performance. *Management Science*, *54*(7), 1213–1230.

Groysberg, B., Polzer, J. T., & Elfenbein, H. A. (2011). Too many cooks spoil the broth: How high-status individuals decrease group effectiveness. *Organization Science*, *22*(3), 722–737.

Gruber, M., MacMillan, I. C., & Thompson, J. D. (2012). From minds to markets how human capital endowments shape market opportunity identification of technology start-ups. *Journal of Management*, *38*(5), 1421–1449.

Gruber, M., MacMillan, I. C., & Thompson, J. D. (2013). Escaping the prior knowledge corridor: What shapes the number and variety of market opportunities identified before market entry of technology start-ups? *Organization Science*, *24*(1), 280–300.

Guimerà, R., Uzzi, B., Spiro, J., & Amaral, L. A. N. (2005). Team assembly mechanisms determine collaboration network structure and team performance. *Science*, *308*(5722), 697–702.

Hambrick, D. C. (1994). Top management groups: A conceptual integration and reconsideration of the" team" label. *Research in Organizational Behavior*, *16*, 171–171.

Hamilton, B. H., & Nickerson, J. A. (2003). Correcting for Endogeneity in strategic management research. *Strategic Organization*, *1*(1), 51–78.

Hargadon, A. B. (2002). Brokering knowledge: Linking learning and innovation. *Research in Organizational Behavior*, *24*, 41–85.

He, J., & Huang, Z. (2011). Board informal hierarchy and firm financial performance: Exploring a tacit structure guiding boardroom interactions. *Academy of Management Journal*, *54*(6), 1119–1139.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the Econometric Society*, *47*(1), 153–161.

Hess, A. M., & Rothaermel, F. T. (2011). When are assets complementary? Star scientists, strategic alliances, and innovation in the pharmaceutical industry. *Strategic Management Journal*, *32*(8), 895–909.

Higgins, M. C., & Gulati, R. (2003). Getting off to a good start: The effects of upper echelon affiliations on underwriter prestige. *Organization Science*, *14*(3), 244–263.

Higgins, M. J., Stephan, P. E., & Thursby, J. G. (2011). Conveying quality and value in emerging industries: Star scientists and the role of signals in biotechnology. *Research Policy*, *40*(4), 605–617.

Hogan, R., & Hogan, J. (2002). Leadership and socio-political intelligence. In R. Riggio, S. Murphy, & F. Pirozzolo (Eds.), *Multiple intelligences and leadership* (pp. 75–88). Mahwah, NJ: Erlbaum.

Johnson, C., Funk, S., & Clay-Warner, J. (1998). Organizational contexts and conversation patterns. *Social Psychology Quarterly*, *61*, 361–371.

Joshi, A., & Knight, A. P. (2015). Who defers to whom and why? Dual pathways linking demographic differences and dyadic deference to team effectiveness. *Academy of Management Journal*, *58*(1), 59–84.

Jung, H., Vissa, B., & Pich, M. (2017). How do entrepreneurial founding teams allocate task positions? *Academy of Management Journal*, *60*(1), 264–294.

Katila, R., Rosenberger, J. D., & Eisenhardt, K. M. (2008). Swimming with sharks: Technology ventures, defense mechanisms and corporate relationships. *Administrative Science Quarterly*, *53*(2), 295–332.

Katila, R., & Shane, S. (2005). When does lack of resources make new firms innovative? *Academy of Management Journal*, *48*(5), 814–829.
Kehoe, R. R., & Tzabbar, D. (2015). Lighting the way or stealing the shine? An examination of the duality in star scientists' effects on firm innovative performance. *Strategic Management Journal*, *36*(5), 709–727.
Kennedy, P. (2008). *A Guide to Econometrics*. Oxford: Blackwell Publishing.
Kilduff, G. J., Willer, R., & Anderson, C. (2016). Hierarchy and its discontents: Status disagreement leads to withdrawal of contribution and lower group performance. *Organization Science*, *27*(2), 373–390.
Klepper, S., & Sleeper, S. (2005). Entry by spinoffs. *Management Science*, *51*(8), 1291–1306.
Knight, R. M. (1989). Technological innovation in Canada: A comparison of independent entrepreneurs and corporate innovators. *Journal of Business Venturing*, *4*(4), 281–288.
Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *RAND Journal of Economics*, *31*(4), 674–692.
Lacetera, N., Cockburn, I. M., & Henderson, R. (2004). Do firms change capabilities by hiring new people? A study of the adoption of science-based drug discovery. *Advances in Strategic Management*, *21*, 133–159.
Li, G.-C., Lai, R., D'Amour, A., Doolin, D. M., Sun, Y., Torvik, V. I., … Fleming, L. (2014). Disambiguation and co-authorship networks of the U.S. patent inventor database (1975–2010). *Research Policy*, *43*(6), 941–955.
Li, Y., Li, N., Li, C., & Li, J. (in-press). The boon and bane of creative “stars”: A social network exploration of how and when team creativity is (and is not) driven by a star teammate. *Academy of Management Journal*. https://doi.org/10.5465/amj.2018.0283
Loch, C. H., Huberman, B. A., & Stout, S. (2000). Status competition and performance in work groups. *Journal of Economic Behavior & Organization*, *43*(1), 35–55.
Magee, J. C., & Galinsky, A. D. (2008). Social hierarchy: The self-reinforcing nature of power and status. *The Academy of Management Annals*, *2*(1), 351–398.
March, J. G., & Simon, H. A. (1958). *Organizations*. New York: John Wiley.
Matusik, S. F. (2002). An empirical investigation of firm public and private knowledge. *Strategic Management Journal*, *23*(5), 457–467.
McDougall, P., & Robinson, R. B. (1990). New venture strategies: An empirical identification of eight ‘archetypes’ of competitive strategies for entry. *Strategic Management Journal*, *11*(6), 447–467.
Mowery, D. C., Oxley, J. E., & Silverman, B. S. (1996). Strategic alliances and interfirm knowledge transfer. *Strategic Management Journal*, *17*(S2), 77–91.
Nerkar, A. A., McGrath, R. G., & MacMillan, I. C. (1996). Three facets of satisfaction and their influence on the performance of innovation teams. *Journal of Business Venturing*, *11*(3), 167–188.
Newman, M. E., Watts, D. J., & Strogatz, S. H. (2002). Random graph models of social networks. *Proceedings of the National Academy of Sciences*, *99*(suppl 1), 2566–2572.
Oettl, A. (2012). Reconceptualizing stars: Scientist helpfulness and peer performance. *Management Science*, *58*(6), 1122–1140.
Onal Vural, M., Dahlander, L., & George, G. (2013). Collaborative benefits and coordination costs: Learning and capability development in science. *Strategic Entrepreneurship Journal*, *7*(2), 122–137.
Ott, T. E., Eisenhardt, K. M., & Bingham, C. B. (2017). Strategy formation in entrepreneurial settings: Past insights and future directions. *Strategic Entrepreneurship Journal*, *11*(3), 306–325.
Overbeck, J. R., Correll, J., & Park, B. (2005). Internal status sorting in groups: The problem of too many stars. In M. Neale, E. Mannix, & M. C. Thomas-Hunt (Eds.), *Research on managing groups and teams* (pp. 171–201). Greenwich, CT: JAI Press.
Pahnke, E. C., McDonald, R., Wang, D., & Hallen, B. (2015). Exposed: Venture capital, competitor ties, and entrepreneurial innovation. *Academy of Management Journal*, *58*(5), 1334–1360.
Park, A. E., & Lee, T. H. (2011). Evolution of minimally invasive surgery and its impact on surgical residency training. In R. Matteotti & S. W. Ashley (Eds.), *Minimally invasive surgical oncology* (pp. 11–22). New York, NY: Springer.
Park, H. D., & Tzabbar, D. (2016). Venture capital, CEOs' sources of power, and innovation novelty at different life stages of a new venture. *Organization Science*, *27*(2), 336–353.
Paruchuri, S. (2010). Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. *Organization Science*, *21*(1), 63–80.
Pfeffer, J. (1981). *Power in organizations*. Marshfield, MA: Pitman.
Phelps, C. C. (2010). A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. *Academy of Management Journal*, *53*(4), 890–913.
Polanyi, M. (1966). The logic of tacit inference. *Philosophy*, *41*(155), 1–18.
Reagans, R., Argote, L., & Brooks, D. (2005). Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management Science*, *51*(6), 869–881.

Reagans, R., & Zuckerman, E. W. (2001). Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organization Science*, *12*(4), 502–517.

Ridgeway, C., & Johnson, C. (1990). What is the relationship between socioemotional behavior and status in task groups? *American Journal of Sociology*, *95*(5), 1189–1212.

Ridgeway, C. L., Johnson, C., & Diekema, D. (1994). External status, legitimacy, and compliance in male and female groups. *Social Forces*, *72*(4), 1051–1077.

Roberts, E. (1991). *Entrepreneurs in high technology, Lessons from MIT and beyond*. New York: Oxford University Press.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal*, *9*(1), 86–136.

Rosenkopf, L., & Almeida, P. (2003). Overcoming local search through alliances and mobility. *Management Science*, *49*(6), 751–766.

Rothaermel, F. T., & Hess, A. M. (2007). Building dynamic capabilities: Innovation driven by individual-, firm-, and network-level effects. *Organization Science*, *18*(6), 898–921.

Sauermann, H., & Cohen, W. M. (2010). What makes them tick? Employee motives and firm innovation. *Management Science*, *56*(12), 2134–2153.

Schoonhoven, C. B., Eisenhardt, K. M., & Lyman, K. (1990). Speeding products to market: Waiting time to first product introduction in new firms. *Administrative Science Quarterly*, *35*(3), 177–207.

Scott, W. R. (1966). Professionals in bureaucracies-areas of conflict. In H. M. Vollmer & D. L. Mills (Eds.), *Professionalization* (pp. 265–275). New Jersey: Prentice Hall: Englewood Cliffs.

Simon, H. A. (1991). Bounded rationality and organizational learning. *Organization Science*, *2*(1), 125–134.

Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality? *Management Science*, *56*(1), 41–56.

Smith, S. W., & Shah, S. K. (2013). Do innovative users generate more useful insights? An analysis of corporate venture Capital Investments in the Medical Device industry. *Strategic Entrepreneurship Journal*, *7*(2), 151–167.

Sørensen, J. B. (2007). Bureaucracy and entrepreneurship: Workplace effects on entrepreneurial entry. *Administrative Science Quarterly*, *52*(3), 387–412.

Stinchcombe, A. L. (1959). Bureaucratic and craft administration of production: A comparative study. *Administrative Science Quarterly*, *4*, 168–187.

Stuart, T. E., Hoang, H., & Hybels, R. C. (1999). Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly*, *44*(2), 315–349.

Stuart, T. E., & Podolny, J. M. (1996). Local search and the evolution of technological capabilities. *Strategic Management Journal*, *17*(S1), 21–38.

Suarez, F. F., Cusumano, M. A., & Kahl, S. J. (2013). Services and the business models of product firms: An empirical analysis of the software industry. *Management Science*, *59*(2), 420–435.

Subramanian, A. M., Lim, K., & Soh, P.-H. (2013). When birds of a feather don't flock together: Different scientists and the roles they play in biotech R&D alliances. *Research Policy*, *42*(3), 595–612.

Taylor, A., & Greve, H. R. (2006). Superman or the fantastic four? Knowledge combination and experience in innovative teams. *Academy of Management Journal*, *49*(4), 723–740.

Toole, A. A., & Czarnitzki, D. (2009). Exploring the relationship between scientist human capital and firm performance: The case of biomedical academic entrepreneurs in the SBIR program. *Management Science*, *55*(1), 101–114.

Tushman, M., & O'Reilly, C. (1996). Evolution and revolution: Mastering the dynamics of innovation and change. *California Management Review*, *38*(4), 8–30.

Tzabbar, D., & Kehoe, R. R. (2014). Can opportunity emerge from disarray? An examination of exploration and exploitation following star scientist turnover. *Journal of Management*, *40*(2), 449–482.

Udy, S. H. (1959). " bureaucracy" and" rationality" in Weber's organization theory: An empirical study. *American Sociological Review*, *24*, 791–795.

Uotila, J., Maula, M., Keil, T., & Zahra, S. A. (2009). Exploration, exploitation, and financial performance: Analysis of S&P 500 corporations. *Strategic Management Journal*, *30*(2), 221–231.

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica: Journal of the Econometric Society*, *57*(2), 307–333.

Wasserman, N. (2003). Founder-CEO succession and the paradox of entrepreneurial success. *Organization Science*, *14*(2), 149–172.

Wasserman, N. (2012). *The founder's dilemmas: Anticipating and avoiding the pitfalls that can sink a startup*. Princeton, NJ: Princeton University Press.

Wasserman, N. (2017). The throne vs. the kingdom: Founder control and value creation in startups. *Strategic Management Journal*, *38*(2), 255–277.

Whyte, W. F. (1943). *Street corner society; the social structure of an Italian slum*. Chicago, IL: University of Chicago Press.

Winter, S. G., Cattani, G., & Dorsch, A. (2007). The value of moderate obsession: Insights from a new model of organizational search. *Organization Science*, *18*(3), 403–419.
Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.
Zucker, L. G., Darby, M. R., & Armstrong, J. (1998). Geographically localized knowledge: Spillovers or markets? *Economic Inquiry*, *36*(1), 65–86.
Zucker, L. G., Darby, M. R., & Armstrong, J. S. (2002). Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. *Management Science*, *48*(1), 138–153.

How to cite this article: Lahiri A, Pahnke EC, Howard MD, Boeker W. Collaboration and informal hierarchy in innovation teams: Product introductions in entrepreneurial ventures. *Strategic Entrepreneurship Journal*. 2019;13:326–358. https://doi.org/10.1002/sej.1331