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Where Do Stars Come From? The Role of Star versus Non-Star Collaborators in Creative Settings

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Creative stars make disproportionately influential contributions to their fields. Yet we know little about how an innovator's creative performance is affected by collaborating with stars. This paper studies the creative aspects of interpersonal collaboration from a new perspective: the quality of the collaborator. Both star and non-star collaborators provide different benefits to a focal innovator. The innovator benefits from collaborating with non-stars because they may provide access to diverse information improving performance on the creative task at hand. In contrast, a focal innovator benefits from collaborating with stars because she can then experience and learn the star's superior set of creative skills and thus build lasting creative capabilities. Building on a theoretical argument about those two different collaboration purposes, we first examine how a star collaboration (versus a non-star collaboration) affects a comprehensive measure of an innovator's creativity: the likelihood of emerging as a star. Second, we examine how the different creative benefits of engaging with a star versus a non-star collaborator affect the effect of two widely studied aspects of interpersonal collaboration on star emergence: social network cohesion and expertise similarity. In contrast to collaborations with non-stars, for which social cohesion and expertise similarity limit access to diverse information negatively affecting star emergence, social network cohesion and expertise similarity have a decidedly positive effect on star collaborations by improving the transfer of the star's set of creative skills. Our empirical setting consists of designers who have been granted design patents in the United States from 1975 through 2010.

Keywords: Star; Interpersonal Collaboration Networks; Emergence of Stars; Design Patents; Knowledge Transfer

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1. INTRODUCTION

Previous research has recognized the existence of *creative stars*—or individuals who, by virtue of their extraordinary creative talent, generate disproportionately influential output and thus make outstanding contributions to their fields (Ernst 2001, Godart et al. 2015, Oettl 2012, Zucker et al. 1998). Scholars have shown that stars may enjoy higher social attention, some of which they can bestow on their collaborators (Azoulay et al. 2010, Simcoe and Waguespack 2011); however, we know little about how collaborating with a star affects the creative approaches experienced by a focal innovator and what consequences ensue. In fact, throughout the literature on interpersonal collaboration in creative settings there is an implicit assumption: that the creative approach associated with a star collaboration is not fundamentally different from the one associated with a non-star collaboration (e.g., Burt 2004, Fleming et al. 2007, Obstfeld 2005, Perry-smith 2006, Sosa 2011, Tortoriello et al. 2015, Tortoriello and Krackhardt 2010, Uzzi and Spiro 2005). Our paper challenges this view. We provide evidence that collaborators of different quality (i.e., stars vs. non-stars) induce different ways of innovating, each of which has distinct benefits for the focal innovator. These various benefits induce a distinct outlook for the focal innovator's extraordinary creative performance and thus her propensity to rise to stardom herself.

Many studies that explore the effects of interpersonal collaboration on creative output have focused on examining the "idea generation" phase of innovation (e.g., Burt 2004, Fleming et al. 2007, Girotra et al. 2010, Hargadon and Sutton 1997, Sosa 2011, Tortoriello et al. 2015). This focus on idea generation makes sense given that constructing a wide-ranging pool of potentially innovative ideas increases the odds that one such idea becomes an influential breakthrough innovation (Ahuja and Lampert 2001, Dahan and Mendelson 2001, Girotra et al. 2010, Schumpeter 1934, Singh and Fleming 2010). According to this research stream, the main role played by collaborators is that of providing new information to a focal innovator—information that she can recombine and reconfigure into a stream of new ideas. Thus new information is the raw material, the "ingredients", that innovators combine to form potentially innovative ideas (Ahuja 2000, Burt 2004, Fleming 2001, Perry-smith 2006, Rodan and Galunic 2004, Sosa 2011, Tortoriello et al. 2015). The more diverse this new information, the better the innovator's creative performance and the higher the likelihood of creating a breakthrough innovation (Girotra et al. 2010, Singh and Fleming 2010, Dahlander and Piezunka 2017). It follows that a focal innovator benefits most from collaborators of diverse background and from a collaboration environment that best provides access to diverse ideas. From this perspective, however, no explicit distinctions among levels of collaborator quality (stars vs. non-stars) have been necessary—presumably because that literature has distinguished collaborators mainly by the diversity of ideas they provide and by those aspects of the collaboration that maximize access to diverse ideas.

However, this literature has not addressed *how* the raw information is recombined and assembled into coherent innovations; rather, the recombination of ideas and information has been treated as automatic (i.e., a black box). Yet more recent work exploring creativity has acknowledged how important is the process of synthesizing diverse ideas and pieces of information into a new coherent and holistic solution (Chen and Adamson 2015, Hargadon and Bechky 2006, Harvey 2014, Long-Lingo and O'Mahony 2010). Even though this literature does not negate the value of accessing new diverse information, the emphasis in this literature is on how diverse and sometimes contradictory information can be integrated. From that standpoint, innovators must be able to integrate information effectively—they must have both synthesis knowledge and skills (Ahuja 2000, Harvey 2014, Sutton and Hargadon 1996). In this context, collaborator quality is decisive; creative stars become central.

We argue (and provide empirical evidence) that stars are much more likely to possess the "synthesis knowledge" that enables effective integration of diverse inputs. This knowledge is highly tacit and difficult to acquire—akin to learning how to sculpt a complex shape or how to create vanguard cuisine (Harvey 2014, Kogut and Zander 1992, Svejenova et al. 2007). Therefore, collaborating with those few "masters" who possess synthesis knowledge makes it much more likely for a focal innovator to learn and master the synthesis knowledge and skills that underlie many outstanding innovations. In other words, a focal innovator who collaborates with a star learns synthesis skills from the master while herself undertaking a synthesis for an actual innovation task. The benefits of such guided "learning by doing" in a collaboration with a star is a lasting transformation of the innovator's creative skills (Ainley and Rainbird 2013, von Hippel and Tyre 1995); she is then far more likely to create breakthrough innovations on a consistent basis and, ultimately, to become a creative star herself.

Hence we formulate our paper's central premise as follows: creative star collaborators have a fundamentally different effect on the focal innovator than do non-star collaborators. Non-star collaborators can support an innovator in the creation of outstanding outcomes by providing access to diverse sources of ideas. Such new information is typically context specific (Kogut and Zander 1992) and—even when reused in other contexts (Hargadon and Sutton 1997)—does not improve the focal innovator's ability to create breakthroughs per se. Star collaborators, in contrast, allow the focal innovator to observe, learn, and practice synthesis skills. Collaborating with creative stars provides unique learning opportunities to acquire and develop an exclusive set of synthesis skills that transform and better equip the innovator to develop extraordinary creativity. So if collaborating with a star (vs. a non-star) has such a transformative effect on the focal innovator, then we should expect to see a like effect on the probability of that innovator becoming a star herself.

If the main role of a star collaborator is to provide a salient opportunity for the learning of synthesis knowledge and if a non-star collaborator's main purpose is to provide new (and potentially diverse) information, then the conditions that increase or reduce the benefits of such collaborations should be fundamentally different. We study how two particular factors—which are salient in the literature on interpersonal collaboration in creative settings—relate to an innovator's star emergence as a function of the quality of collaborators (Reagans and McEvily 2003, Gargiulo et al. 2009, Reagans et al. 2015, Tortoriello et al. 2015): *network cohesion*, or the extent to which the focal innovator and her collaborator share common third parties; and *expertise similarity*, or the extent to which the focal innovator and her collaborator share similar past work-related experience.

We establish that, in the absence of a creative star, high levels of network cohesion and expertise similarity actually reduce the focal innovator's likelihood of becoming a creative star. High network cohesion can cause social pressure that steers the collaboration toward convergent "groupthink", and high expertise similarity implies that there will be far fewer recombinant perspectives available to the focal innovator (Janis 1972, Perry-Smith and Shalley 2003, Burt 2004, Fleming et al. 2007). As a result, any innovation effort involving only non-star collaborators will likely be adversely affected by increased levels of network cohesion and expertise similarity.

In contrast, an effective collaboration with a star that helps the focal innovator become a creative star is likely to emphasize the practice and transfer of synthesis knowledge. A cohesive network with a star not only facilitates carrying out the synthesis of potentially creative ideas but also "enforces" cooperative behavior that empowers the effective transfer of tacit knowledge (Hargadon and Bechky 2006, Obstfeld 2005, Reagans and McEvily 2003, Tortoriello et al. 2015, Tortoriello and Krackhardt 2010). Similarly, shared expertise with the creative star establishes a common knowledge base and thus increased absorptive capacity that also facilitates the transfer of creative skills to the focal innovator (Cohen and Levinthal 1990, Reagans and McEvily 2003, Tortoriello 2014). Therefore, that innovator thrives in a star collaboration—perhaps to the extent of becoming a star herself—because network cohesion and expertise similarity facilitate the learning of complex synthesis knowledge, which transforms the focal innovator's creative capability.

Examining these two contingencies is important because they further validate the distinct learning mechanisms that underlie effective star and non-star collaborations. More importantly, that both network cohesion effects and expertise similarity effects change as a function of the collaborator quality suggests that neither is a homogenous construct. Therefore, in conceptualizing them it may be necessary to account for the quality of the actors involved.

We find support for our theoretical arguments in the empirical setting of industrial design, a discipline of increasing relevance to building innovative and competitive capabilities in various industries (Brown 2008, Brunner et al. 2008). Industrial design efforts—which focus on creating new form, not new functionality—can seldom be definitively formulated because the problems are ambiguous and the solutions uncertain. Hence the context of industrial design provides an opportunity to test our arguments related to the distinct nature of interpersonal collaborations with creative stars (Ulrich 2011). Our data on this industry come from the *design* patent database of the US Patent and Trademark Office (USPTO 2015). We processed design patent data for the period 1975–2010 to examine the creative performance of individual designers in a pool of 144,288 designers who had been granted at least one design patent.

2. THEORY AND HYPOTHESES

In what follows we build an argument that star and non-star collaborators have distinct effects on the focal innovator's extraordinary creative outcomes—that is, her emergence as a star. We shall proceed in three steps. First, in line with an emerging literature, we argue that there are two different ways to create breakthrough innovations; of these, perhaps the more reliable is the one requiring a specific set of skills. We then argue that the exceptional creative talent of stars is an example of such creative skills. Finally, we posit that the focal innovator learns skills of this nature from a star collaborator, which significantly enhances her ability to produce breakthroughs and possibly even emerge as a star in her own right.

Two ways to create a breakthrough innovation. The extant literature has established that collaborating with others (rather than working as a lone inventor) increases the chances that the innovator creates a breakthrough (Ahuja and Lampert 2001, Singh and Fleming 2010, Uzzi et al. 2013, Wuchty et al. 2007). Indeed, there is a broad literature informing us about how interpersonal collaboration advances the pursuit of creative endeavors (Burt 2004, Fleming et al. 2007, Obstfeld 2005, Perry-smith 2006, Sosa 2011, Tortoriello et al. 2012, Tortoriello and Krackhardt 2010). This stream of research has, while emphasizing the idea generation phase of development, implicitly adopted an evolutionary view of the creative process. A focal actor exposed to diverse sources of inspiration (e.g., different ideas, different personal backgrounds, different ways of framing problems) is well positioned to identify many new and potentially useful relationships among the diverse sources of inspiration and thus to generate, in turn, many distinct new ideas

(Csikszentmihalyi 1996, Schumpeter 1934, Simonton 1999). If a large enough number of diverse ideas are generated then at least some of them are bound (statistically speaking) to be exceptionally good: these are the breakthroughs (Dahan and Mendelson 2001, Girotra et al. 2010, Singh and Fleming 2010). Following exposure to a pool of diverse ideas, individual innovators who come up with breakthroughs may well become stars.

There have been some recent challenges, however, to conceptualizing the creation of breakthroughs from that evolutionary perspective (Chen and Adamson 2015, Hargadon and Bechky 2006, Harvey 2014, Long-Lingo and O'Mahony 2010). An emerging literature emphasizes a lack of deep understanding of the process that allows innovators to synthesize different ideas into a new holistic solution. For example, Harvey (2014) developed an alternative view—dubbed "creative synthesis"—based on her observations of consistently innovative organizations. According to Harvey (2014), the innovation process of many creative organizations starts with a thorough understanding of the existing paradigm. Then friction with that paradigm emerges as different actors expose inconsistencies in their understanding of it. This friction is the beginning of a dialectical process, the creative synthesis, that develops a novel understanding of the situation by integrating various points of friction into the existing paradigm. The resulting new framework serves to identify innovation opportunities and hence as a map for innovation. A prominent instance of adopting a new innovation map was IBM's move from being a provider of "computing machines" to a company engaged in "the business of information" (Harvey 2014, p. 330). From a new innovation map, innovators derive guidance on constructing *exemplars*: instantiations of a new understanding in the form of a practical product. Multiple exemplars can be derived from the new framework, yet those instantiations may themselves trigger new insights and hence (via another round of the dialectic process) evolve and refine the very framework that first generated the exemplars. Thus innovators can iteratively produce a set of high-potential ideas, refine them, and increase the likelihood of producing not just one breakthrough but a series of them. Of course, an innovator who consistently produces breakthrough inventions is far more likely than others to become a star.

Although one may challenge the completeness of Harvey's model (Chen and Adamson 2015), it clearly identified a neglected aspect of creative interactions and, in doing so, introduced a fundamentally new perspective. The model highlighted that any creative process requires an extensive set of skills and knowledge so that creative input can be synthesized into coherent innovative outcomes (Hargadon and Bechky 2006, Long-Lingo and O'Mahony 2010). For example, Harvey (2014) argued that each iteration of creative synthesis is aided by three sets of process facilitators: collective attention, enacting ideas, and building on similarities. *Collective attention* helps to build an intellectual understanding of the existing paradigm or to "steer" the identification of areas of disillusionment with that paradigm. *Enacting ideas* brings ideas closer to realization; this process consists of posing difficult questions, building tangible representations of ideas (e.g., mock-ups, prototypes, experiments), and gathering and interpreting insights from those tangible representations. Enacting ideas exposes underlying assumptions and unforeseen problems (Bechky 2003, Seidel and O'Mahony 2014) and also builds a deeper and shared understanding of a problem and/or its solution (Nicolini et al. 2012). Finally, *building on similarities* allows collaborators to see the connections between disparate perspectives. This process helps frame ideas in terms of the other person's frame of reference, thereby rendering them subjects of meaningful communication and thus of creative synthesis (Reagans and McEvily 2003).

These facilitators make clear that intricate skills are required to master a process like creative synthesis, which raises the question of how an innovator can acquire such skills. We shall argue that creative stars are more likely than others to have developed creative synthesis skills and that innovators who work closely with stars are more likely (than innovators who have not) to experience and internalize those skills.

Creative stars and creative synthesis skills. Creative stars possess skills that make them especially adept at performing and guiding creative synthesis. Stars are better than non-stars at focusing collective attention: first on "what is", in order to understand the status quo; and then on "what could be", in order to trigger innovation. Stars are consummate questioners with a passion for challenging standard assumptions; not only do star innovators ask more questions than non-star innovators, they also ask more provocative ones.

Hargadon and Bechky (2006, p. 492) described moments of collective creativity as involving “not only the original question, but also [considering] whether there is a better question to be asked.” Stars are more likely to “fundamentally reassess the purpose, function or use of a product” (Cross 2003, p. 6). Such questioning may open up new and/or unexpected possibilities. Stars also steer collective attention by facilitating (and leading) cognitive group processes. They attend to ideas in a way that each member can understand (Vera and Crossan 2005), which helps their collaborators make meaningful connections to others’ ideas. Stars thus can help bridge gaps in understanding between collaborators and facilitate communication that pushes the innovation effort forward (Bartunek 1984).

In addition, creative stars are better than non-stars at enacting ideas. For many potentially fruitful problems, both the problem statement and the solution space are open ended; hence making progress requires a thorough understanding of the context to even define the problem properly. Stars are much more likely than others to decompose complex and poorly defined problems so that they become clear and well defined (Ho 2001). Stars often reformulate the problem to add structure (Eckert et al. 2002); in this, they focus on what rules to break, whereas non-stars—more often than not—conform to those rules (Weisberg 1999). Stars have a particular talent for identifying those aspects in a solution proposal that are most in need of questioning and verification. Stars are typically obsessed with building the actual enactment and encouraging the search for insights from the evaluation of prototypes. Eckert and Stacey (2002) found that highly skilled designers, in their quest for novelty, use prototypes more creatively than do less skilled designers.

Creative stars are better than non-stars at building on similarities. Put simply, innovative thinkers are able to connect fields, problems, and ideas that others perceive as being unrelated (Mednick 1962). Not only do they have deeper knowledge, but that knowledge is cognitively organized in ways that make it more accessible and functional and thus a more efficient facilitator of future recombination (Bédard and Chi 1992). Stars tend to store knowledge based on meaning, concepts, and principles, an approach that allows for a more thorough and useful cross-referencing of the knowledge they possess (Bordage and Zacks 1984, Chi et al. 1981). As a result, stars can see more profound connections between ideas and are better prepared to integrate opposing dialectic opinions.

Finally, stars are better at pacing the entire iterative creative process (Lloyd and Scott 1994). They intuit when to initiate what aspect in the creative journey, when to continue evaluating ideas, and when to start enacting ideas (Ahmed et al. 2003). Stars are not averse to triggering rework for others, which restarts the entire "enacting ideas" cycle (Sosa 2014). Most importantly, stars are often more persistent than non-stars at working with a principal concept and are more reluctant to quickly generate alternatives; thus a star will pursue his principal solution concept for as long as possible and even in the face of unexpected difficulties (Cross 2004).

Learning creative synthesis from creative stars. The aforementioned skills make stars exceptionally good at creative synthesis. This skill set could, in principle, be discovered and mastered by any innovator through individual trial and error or via collaboration with non-stars. Yet as implied by the preceding discussion, creative synthesis skills are both tacit and intricately linked. It follows that learning them is unlikely to occur through either self-discovery or codified methods (Kogut and Zander 1992). Instead, it is by close-up observation and emulation that a focal innovator learns such a special set of skills. Interpersonal collaboration is an ideal environment for learning by doing under a star's guidance (Ainley and Rainbird 2013, Dougherty 1992, von Hippel and Tyre 1995).

Suppose, for example, an innovator is learning the skill of focusing collective attention on "what is" and "what could be". If this innovator collaborates with a star then she can observe how the star asks questions to foster a common understanding of what is; she can also observe how the star thinks about potential improvements to the existing paradigm and experience how the star steers discussions with collaborators that both bridge the gaps between different viewpoints and allow those collaborators to assimilate behaviors that are difficult to explain in words. Now consider an innovator who is learning the skills and behaviors that support enacting ideas. Observing creative stars approach an ill-defined problem, decide on what to focus when building initial prototypes, and collect feedback from prototypes provides a learning experience that can hardly be matched by collaboration with non-stars. Finally, consider learning the stars' approach to building on similarities. Seeing creative stars reconcile and connect ideas, seeing the questions they ask, and observing their frame of mind when they connect ideas enables collaborators to construct templates for future behavior. Overall, the future of any innovator is enhanced by learning how to engage in creative synthesis, how to derive exemplars from the new understanding that results, and how to identify circumstances under which iteration in search of new options is (or is not) advisable.

Putting it all together. A focal innovator benefits from collaborating with other non-stars mainly because such collaborations can be catalysts of divergent idea generation, from which creative sparks can lead to a breakthrough idea. In contrast, the innovator benefits from collaborating with a star not only because it will likely improve idea generation but also because she can experience and learn creative synthesis skills. In this sense, the potential benefits of collaborating with a star go beyond the specific context of that collaboration; in particular, such collaborating equips the focal innovator with a skill set that allows her to generate a series of breakthroughs and rise to star status herself. As a result, the innovator's long-term creative performance—and therefore her likelihood of becoming a star—depends on the quality of her collaborators (i.e., star vs. non-stars).[1] We thus formulate our first hypothesis.

> **Hypothesis 1 (H1)** *A focal innovator is more likely to become a star after collaborating with a creative star than after collaborating with a non-star.*

From the perspective of knowledge transfer, non-star collaborators support a focal innovator's star emergence primarily by opening up access to diverse sources of knowledge whereas star collaborators support star emergence primarily by furthering the transfer of creative synthesis skills; hence the focal

[1] Another mechanism that could plausibly explain the differences between star and non-star collaborations is the possibility of social attention being transferred from the star to his collaborators (Simcoe and Waguespack 2011), which might (or might not) be correlated with the transfer of creative skills we invoked when arguing for Hypothesis 1. Other innovators could view the focal innovator as more capable simply because of her association with a star. In this case, a star's association lends public credibility to the focal innovator because a star's endorsement carries more weight in the community than do endorsements from non-stars (Stewart 2005). It is likely that the "social attention transfer" mechanism, which operates outside the focal dyad, is mostly independent of the within-dyad mechanism of transferring tacit creative synthesis knowledge, which is why we do not discuss the former mechanism from a theoretical viewpoint. However, we account for it in our empirical section.

innovator benefits from these two types of interpersonal collaboration (star vs. non-star) for distinct reasons. As a result, the contextual factors often invoked when examining the determinants of successful knowledge transfer may have diametrically opposed effects. Toward the end of an improved understanding of such differences, we study two of the most salient contextual factors present in interpersonal collaborations: social network cohesion and expertise similarity (Argote et al. 2003, Reagans 2005, Reagans and McEvily 2003, Sosa 2011, Tortoriello et al. 2012).

We focus on these particular factors for two important reasons. First, previous research has shown that—despite a high correlation between the social and knowledge structures of interpersonal relations—those structures are conceptually different and have complementary effects on dyadic knowledge transfer (McEvily et al. 2012, Reagans et al. 2015, Reagans and McEvily 2003, Rodan and Galunic 2004, Sosa 2011, Tortoriello et al. 2012). Second, previous studies have shown that social network and knowledge structures each play both supporting and hindering roles as a function of the interpersonal relation's nature or the characteristics of the knowledge being transferred (Ahuja 2000, Burt 2005, Fleming et al. 2007, Tortoriello et al. 2015). Therefore, we have grounds to believe that these two contextual factors will affect the focal innovator's chances of becoming a star differently for non-star versus star collaborations.

Social network cohesion. Social network cohesion characterizes the extent to which two individuals are connected through common third parties (Coleman 1988, Gargiulo et al. 2009, Tortoriello et al. 2012). If network cohesion is high, then a large proportion of the focal innovator's collaborators also collaborate with each other. If network cohesion is low, then the focal innovator and her collaborators work mostly with different people who are not connected among themselves; in this case, the network has many "structural holes" around the focal innovator (Burt 1992).

Network cohesion is known to have negative *and* positive effects on creative performance (Burt 2005, Fleming et al. 2007, Sosa 2011, Tortoriello et al. 2015). Low levels of social network cohesion have been associated with the creation of potentially creative ideas, since the focal innovator can connect ideas from non-redundant idea sources (Burt 2004, Fleming et al. 2007). Yet low network cohesion levels also weaken the establishment of a supporting environment, which is needed to nurture creative ideas (Obstfeld 2005, Tortoriello et al. 2015, Tortoriello and Krackhardt 2010, Uzzi and Spiro 2005). In what follows we describe the contrasting effects of social network cohesion on the focal innovator's emergence as a star depending on whether she previously collaborated with a star or with non-stars.

When a focal innovator collaborates with a non-star, social conditions that increase the chances of her becoming a star are those that foster the generation of divergent ideas—as when a collaborator's ideas stimulate her divergent thinking. The aim is to increase variance in the ideas generated. In a dense network, however, most collaborators share a mind-set that reflects common beliefs and experiences. So in a highly cohesive network, collaborators begin to resemble one another in terms of their thoughts, actions, and/or knowledge. Such a network around the focal innovator and her non-star collaborator may therefore lead to groupthink (Janis 1972). Because network cohesion thereby reduces the potential for divergent idea generation, it could limit the potential for breakthrough innovations and thus hinder the focal innovator from emerging as a star (Singh and Fleming 2010).

In contrast, if a focal innovator collaborates with a star then the benefits of collaboration depend on the application of creative synthesis as well as on the effective transfer of knowledge and skills associated with creative synthesis. In that sense, high levels of social network cohesion with a star have two benefits. First, they provide supportive conditions for implementing creative synthesis. If a focal innovator collaborates with a star and if that pair is embedded within a cohesive network of collaborators, then it is easier to build a common understanding of the current paradigm and to agree on which of its aspects should be changed; thus cohesion enables and enhances collective attention, which is the first enabling factor of creative synthesis. A close and cohesive collaborative relationship creates a supportive environment for giving and responding to feedback, which allows collaborators to recognize when further concept iteration is necessary (Reagans and McEvily 2003, Sosa 2014). Candid feedback is therefore crucial for enacting ideas—the second enabling factor of creative synthesis. Finally, a cohesive environment supported by a dense network of common collaborators surrounding the focal innovator and the star encourages collaborators to seek similarities among their different perspectives (Reagans and McEvily 2003, Tortoriello et al. 2015); this dynamic furthers the notion of building on similarities, which is the third tenet of creative synthesis.

The second way in which social network cohesion benefits creative synthesis is through its role in the transfer of tacit knowledge and skills from the star to the focal innovator. For such a transfer to be effective, there must be both active cooperation and mutual trust between the collaborators—especially when one considers the complex and tacit nature of creative synthesis knowledge and skills (Hansen 1999). An increased presence of common third parties encourages trust between collaborators (Coleman 1988) and increases the willingness to share creative synthesis knowledge on the star's side (Tortoriello et al. 2012). All this eases the transfer of knowledge from star to focal innovator (Reagans and McEvily 2003). Simply put, our theory postulates that social network cohesion has a positive (resp. negative) effect on star (resp. non-star) collaborations of the focal innovator. We hence hypothesize:

> **Hypothesis 2 (H2)** *The focal innovator's emergence as a star is affected in opposite ways by her social network cohesion with star versus non-star collaborators:*
>
> **H2a** *The focal innovator's likelihood of becoming a star is negatively associated with increasing network cohesion with non-star collaborators.*
>
> **H2b** *The focal innovator's likelihood of becoming a star is positively associated with increasing network cohesion with star collaborators.*

Expertise similarity. A similar line of argument as for social network cohesion applies to the effect of expertise similarity. As innovators accumulate expertise in various aspects of their field (e.g., techniques, industries, types of products), they may encounter opportunities to collaborate with colleagues of similar or different backgrounds. We therefore define *expertise similarity* as the extent to which the focal innovator's expertise is in areas similar to her collaborator's areas of expertise (Reagans 2005, Reagans and McEvily 2003, Singh and Fleming 2010).

When a focal innovator collaborates with a non-star collaborator, the collaboration thrives on access to divergent sources of information; such access increases the odds of the focal innovator establishing novel and useful connections between previously unconnected ideas. In such settings, high levels of expertise similarity are likely to be detrimental. A lack of divergent experiences and backgrounds leads to fewer alternative perspectives and thus fewer opportunities to find novel combinations of knowledge (Ahuja 2000, Dougherty 1992, Hargadon and Sutton 1997, Obstfeld 2005, Perry-smith 2006, Tortoriello et al. 2015). Expertise similarity thus hinders the generation of potentially creative ideas and so limits a focal innovator's chances to achieve stardom.

When the focal innovator collaborates with a star, engaging in creative synthesis and learning the skills associated with creative synthesis become the most prominent mechanisms by which an innovator emerges as a star. In such collaborations, higher levels of expertise similarity are likely to be beneficial. They support all three creative synthesis' facilitators (collective attention, enacting ideas, building on similarities) because a common "idea space" furthers meaningful communication and thus the reconciliation of seemingly contradictory perspectives (Katila and Ahuja 2002, Reagans 2005). Expertise similarity also expedites the transfer of knowledge and skills about creative synthesis from the star to the focal innovator. A focal innovator must appraise, adapt, and ultimately transform her observations of a star engaged in creative synthesis if she seeks to apply creative synthesis skills in her own context. It is easier to adapt new knowledge when it is associated with familiar ideas and concepts (Ahuja and Katila 2001, Cohen and Levinthal 1990, Tortoriello 2014, Tortoriello et al. 2015). Common frameworks, heuristics, and coding schemes make knowledge transfer more effective and efficient (Bechky 2003, Carlile 2004, Dougherty 1992). As a consequence, learning creative synthesis in the context of well-understood fields of expertise is much easier than learning while also engaged in decoding and building contextual knowledge. This generalization holds particularly for learning creative synthesis because most such knowledge is tacit and/or complex (Hansen 1999, Kogut and Zander 1992). In short, expertise similarity facilitates the focal innovator's learning of creative synthesis and therefore increases her chances of becoming a star.

Given these considerations, our theory postulates that expertise similarity has a positive (resp. negative) effect on star (resp. non-star) collaborations of the focal innovator.

Hypothesis 3 (H3) *The focal innovator's emergence as a star is affected in opposite ways by her expertise similarity with star versus non-star collaborators:*

H3a *The focal innovator's likelihood of becoming a star is negatively associated with increasing expertise similarity with non-star collaborators.*

H3b *The focal innovator's likelihood of becoming a star is positively associated with increasing expertise similarity with star collaborators.*

3. DATA, METHODS, AND ANALYSES

To test our hypotheses, we need a longitudinal data set in a creative setting with a large number of repeated observations at the individual level. The data should enable us to identify each designer uniquely, to track each designer's work over time, to identify those who collaborated on that work, and—crucially—to evaluate output objectively. Design patent data fulfill these requirements. Such data contain detailed information on patent designers' names and locations as well as on each patent's application date, content classification, assignee organization (i.e., the entity to which the patent is granted), and citations to other patents. The rich information embedded in design patent data is one of the few publicly available sources that has documented creative design output en masse (Chan et al. 2017).

3.1. Design patents

In the United States, a design patent can be granted for a "new, original, and ornamental design for an article of manufacture" (USPTO 2015). In general terms, a design patent protects the form of an item whereas a utility patent protects an item's functionality. Because design patents focus on innovation in form, not function, their scope is limited to the "overall ornamental visual impression" (USPTO 2015). Design patents provide the ideal context for testing our theory because of design's paradoxical nature: it seeks to find higher-order solutions that accommodate seemingly opposed forces. Buchanan (1992) referred to design as "dialectic" because it occurs at the intersection of constraint, contingency, and possibility. It follows that creative synthesis skills are a fundamental prerequisite to excelling in the field of industrial design.

Although our study is one of the first ones in using design patent data, we can draw on and extend methods developed in the context of utility patents. First, the data's longitudinal nature provides rich historical information at both the personal and network levels. Patent applications allow us to track a designer's collaborators, which means that we can construct a comprehensive collaborative history for each designer in our database.[2] Second, there is a tradition of using patent data to analyze creativity because such data make it possible to quantify creative output and so substantially reduce the difficulty of measuring innovation (Ahuja 2000). We use patent citations as a proxy for the influence of an invention—and hence of its inventor(s). So the more citations a patent receives, the more it is viewed as an inspiration for subsequent creative endeavors (Audia and Goncalo, 2007). The citations that a patent receives are therefore widely viewed as reliable and systematic indicators of an invention's economic, social, and technological success (Jaffe et al. 2002, Singh and Fleming 2010).

3.2. Identifying the emergence of star designers

We define the *popularity index* of a designer at any moment in time by counting the citations received, excluding self-citations, by that designer's patents in the preceding three-year rolling window (Ahuja 2000). An inventor whose popularity index is in the top 2% of all inventors is considered, at the time of measurement, to be a star designer. Operationalizing "star" in this way accords with related literature. Ahuja and Lampert (2001) use the top 1% (of the distribution of patent citations) as their threshold when defining a breakthrough invention, and Singh and Fleming (2010) use a 5% cutoff. As for the relevant time span, scholars who study archival data have used windows ranging from three years (Fleming et al. 2007) to five years (McFayden and Cannella 2004) when assessing an inventor's performance. For robustness, we set the cutoffs at 1%, 2%, and 5% of the distribution with a three-year rolling window; in addition, at the 2% cutoff we compared rolling time windows of three, five, and seven years (as well as *no* rolling window). These alternatives did not yield qualitatively different results.[3]

We define the emergence of a star designer—or the transition from designer to star—as an *event* in the designer's career. This event corresponds to the day when the designer's popularity index first attains the

[2] We adopt and extend the inventor-matching algorithm of Fleming et al. (2007) to disambiguate the names of designers in the design patent database. That algorithm has been employed in a number of related studies and has been extensively refined over the years (Singh and Fleming, 2010; Trajtenberg et al. 2006).

[3] It is reassuring to know that our method correctly identified such well-known star designers such as Yves Behar, Robert Brunner, Jony Ive, Steve Jobs, Frank Nuovo, and Phillippe Starck—to name (alphabetically) just a few.

2% threshold. Although we processed all the design patents granted in the United States during the 1975–2010 period, our observation window ranges from year 1985 to year 2004 because we need to allow for some time before and after that window for designers to accumulate enough citations to establish a stable popularity index. In our observation window, 144,288 designers were granted at least one design patent. Of these, we identified 9,971 star designers (about 7% of the sample).[4] This proportion is in line with previous research, which has pegged the prevalence of extreme performers at values ranging from 0.75% to 10% (Ernst et al. 2000, Groysberg et al. 2011, Zucker et al. 1998). Following prior research that has examined stars (Grigoriou and Rothaermel 2014, Groysberg et al. 2011), we assume that a star designer will remain a star throughout the study's observation window.

3.3. Collaborating with a star designer

Before we can test our hypotheses in Section 3.4, we need to discuss a coarsened exact matching (CEM) sampling method that allows us to mitigate potential concerns about the selection bias inherent in collaborative settings.

Our baseline hypothesis (H1) argues that a focal designer's chances of emerging as a star are substantially greater after collaborating with a star designer than with a non-star designer. Perhaps the foremost challenge in testing such a hypothesis is the possibility that a designer's inherent capabilities (quality) drive not only her chance of working with a star but also the likelihood of emerging as a star herself. We address this endogeneity concern by employing a CEM procedure to identify a sample in which selection issues are significantly mitigated (Azoulay et al. 2010, Iacus et al. 2012, Oettl 2012, Singh and Agrawal 2010). This procedure helps us balance the (pre-treatment) focal and control subsamples by constructing matched pairs that are "statistical twins" in the period *prior* to the focal designer's first star collaboration (the treatment event). Because collaborating with a star is the treatment event in our sample, the two members of each

[4] This proportion is not at odds with our definition of a star: the 7% figure is the average percentage of stars over all our observations, whereas the 2% figure is the "instantaneous" percentage for any given time.

matched designer pair are similar in terms of certain observable pre-treatment variables; they differ only in that one designer in each pair undergoes the treatment—that is, collaborates with a star.

Constructing the CEM sample requires us to identify key confounders that might be correlated with engaging in a star collaboration and also with the focal designer becoming a star. We therefore consider six individual observable characteristics: (i) year of the focal designer's first patent application; (ii) the designer's "career age"; (iii) number of the focal designer's (non-star) collaborators; (iv) number of patents granted to the focal designer; (v) number of inventors that cite the focal designer's patent(s); and (vi) major patent class(es) to which the designer's patents have been assigned—a categorical variable that captures 33 major design classes (USPTO 2015). We follow Bode et al. (2015) in performing a logit regression to test whether these factors are indeed associated with the probability of collaborating with a star designer. Table 1 reports the results, where the dependent variable is "entering into collaboration with a star designer". In this table, Model [1] (resp. [2]) excludes (resp. includes) the major class dummies. The reported coefficient estimates indicate that our factors are indeed significant determinants of a focal designer's collaborating with a star designer. Hence, when building our CEM sample, we are justified in using these six variables.

Table 1. Logit Regressions on the Antecedents of Collaborating with a Star Designer

Variable	[1]		[2]	
Year of first patent application	-0.014*	(0.007)	-0.01	(0.007)
Career age	0.112***	(0.008)	0.115***	(0.008)
Number of non-guru collaborators	-0.130***	(0.017)	-0.145***	(0.018)
Number of patents	0.053***	(0.013)	0.049***	(0.014)
Number of citers	0.001***	(0)	0.001***	(0)
Major patent class dummies	no		yes	
Log likelihood	-5285		-5169	

Robust standard errors clustered by focal designers shown in parentheses. N = 145,200 designer-patent observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To build the CEM sample we identify pairs of designers who were, in terms of the six key pre-treatment observables, statistically similar at the time of the treatment event (star collaboration). We match the two groups—that is, those who do or do not undergo the treatment event—using exact matches for the first two variables and using four discrete buckets for each of the last four variables. As in the extant literature, we match each treated designer with exactly one control designer so that we need not assign weights to potentially multiple control designers (Azoulay et al. 2010, Singh and Agrawal 2010). Table 2 displays the outcome of our CEM procedure, which splits 14,250 designers into treatment and control groups of equal size. As expected, our matching variables are now almost identically distributed between the treated designers (who end up collaborating with star designers) and the control group (who do not) at the time of that treatment event: their respective covariates are well balanced, and their mean values do not differ significantly (at the 5% level).

Table 2. Summary Statistics for Matched Samples (N= 14,250 designers)

	Treated designers		Control designers	
	Mean	S.D.	Mean	S.D.
Year of first patent application	1997.42	5.14	1997.42	5.14
Career age	1.25	2.91	1.25	2.84
Number of non-star collaborators	3.23	2.91	3.17	3.17
Number of patents	3.49	1.76	3.52	1.87
Number of citers	14.51	46.72	14.06	56.79

3.4. Testing H1 via event history analysis

In this section we test Hypothesis 1 directly by way of an event history analysis that allows us to model precisely the relative likelihood of an event (here, star emergence) over a specific time span while accounting for the difference between censored and uncensored cases (Blossfeld & Rohwer, 1995). Our data are right-censored because information about the event of interest may arrive in the future—as when a designer has not become a star by the end of our observation window but might become one later.

As is customary in event history analysis, we employ maximum likelihood techniques to estimate Cox proportional hazard models on survival-time data (Cox 1972). To control for the non-independence of multiple observations of the same designer and to account for heteroscedasticity, models were estimated with robust standard errors clustered by individual designer. For estimation purposes, we use the *stcox* command in Stata 14.0.

We test H1 using three samples selected via our CEM analysis. These samples reflect different criteria regarding collaboration patterns before the first star collaboration (i.e., prior to the treatment event). In the first sample, each designer had at least one non-star collaborator before the treatment event; this is the CEM sample, described previously, that contains 14,250 designers. Each of the 4,486 designers in the second sample had *no* previous collaboration and so the treatment event constituted the first one. Finally, the third sample simply comprises the previous two and therefore contains 18,736 designers. We use the three samples to compare the effect of star collaboration against two different baselines. Thus the first sample is used to compare the effect of star collaboration against non-star collaboration and the second to compare the effect of star collaboration against no collaboration. We use the third sample to compare the effect of star collaboration against any type of non-star collaboration (including no collaboration).

Formally, we create an indicator variable set to 1 for treated designers (who collaborate with a star designer) or set to 0 for control designers (who do not). We control for other possible sources of heterogeneity in the creative abilities of all the sample's designers by constructing six additional variables described in Table 3.

Table 3. Definition of Control Variables for Testing H1

Assignee's past patents. The assignee is the organization owning the patent and usually the organization with which the designer is associated. The organization's cumulative number of patents until time t is a good proxy for the scale of its innovation activities (Audia and Goncalo 2007) and strongly correlated with its innovativeness (Trajtenberg 1990). More innovative organizations tend to attract and retain the field's best applicants and hence an organization's patent stock is associated with the quality of its staff.
Class diversity. Audia and Goncalo (2007) report that more highly skilled patenting inventors are more likely to venture into different innovation areas making the diversity of classes within which a designer has secured patents a proxy for her capability to think and act in a creative way. Our Class diversity variable is a count of the number of unique subclasses in which a focal designer has been awarded a patent up to time t.
Mobility. The number of firms with which an individual has been associated is strongly correlated with that individual's experience (Fujiwara-Greve and Greve 2000). The Mobility variable counts the number of unique assignees associated with the focal designer until time t.
Location diversity. There is sufficient abundant evidence suggesting that living in diverse locations lets an individual absorb different cultures, gain access to novel ideas, or experience "conceptual expansion" all of which increases individual creativity (Maddux and Galinsky 2009). It thus makes a focal designer more capable. For each designer, we count the number of different states (in the United States) or number of different countries (outside the United States) in which the designer has worked until time t.

Patent stock year. Because the number of patents applied for (and granted) has increased over the years (Trajtenberg 1990), we count, for each year, the total number of patents granted in each major patent class. Then, for each designer we include the count that corresponds to the major class of her patents (at time t).
Cohort. This is a set of dummy variables used to control for when a designer begins to file patents. It indicates whether the designer first patented in one of the five-year intervals during the 1985–2004 period.

Table 4. Descriptive Statistics and Correlation of Variables

	Variable	Mean	S.D.	1	2	3	4	5
1	*Treated designer dummy*	0.56	0.50					
2	*Assignee's past patents*	5.53	4.18	0.00				
3	*Class diversity*	2.65	2.57	0.12	0.00			
4	*Mobility*	1.30	0.81	0.08	0.00	0.46		
5	*Location diversity*	1.03	0.18	0.06	0.00	0.17	0.15	
6	*Patent stock year*	6.72	0.68	0.03	0.03	0.13	0.07	0.03

N=44,320. Correlations greater than |0.003| are significant at $p < 0.05$

Table 5. Proportional Hazard Models Predicting Star Emergence to Test H1

	(1)		(2)		(3)	
	Patents without a star collaborator		**Lone innovator patents**		**All patents**	
Variable	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Treated designer dummy	0.438***	(0.05)	1.243***	(0.095)	0.638***	(0.044)
Controls						
Assignee's past patents	0.003	(0.006)	0.013	(0.01)	0.005	(0.005)
Class diversity	0.306***	(0.028)	0.343***	(0.043)	0.318***	(0.023)
Mobility	0.231***	(0.034)	0.307***	(0.076)	0.226***	(0.031)
Location diversity	0.751***	(0.121)	0.664***	(0.157)	0.714***	(0.099)
Patent stock year	0.652***	(0.058)	0.539***	(0.08)	0.612***	(0.047)
Cohort	yes		yes		yes	
No of subjects	14250		4486		18736	
No of observations	33,861		10,459		44,320	
Log likelihood	-15210		-4795		-20397	

Robust standard errors clustered by focal designer are reported in parentheses. * p<0.10, ** p <0.05, *** p<0.01

Table 4 presents the descriptive statistics for and correlations between our variables, and Table 5 presents the results for the Cox proportional hazard model estimations. The effect of our *Treated designer* dummy variable in all models is positive and significant ($p < .01$), supporting H1. That effect is also significant in models that exclude all controls. In Model [1], where we use the sample in which the treated designer collaborates at least once with a non-star before the treatment event, the dummy indicator has a positive and highly significant coefficient (0.438, $p < .01$). It follows from this model that our treated designers are 55% ($e^{0.438} - 1 = 0.550$) more likely to emerge as a star than our control designers. Model [2] reports corresponding values for when the focal designer worked alone before her first collaboration with a star designer; these values confirm the notion that a star collaboration is more beneficial to star emergence than is not collaborating at all. Hypothesis 1 continues to be supported when instead we use the most general CEM sample, which includes all treated designers; see Model [3].

3.5. Complementary empirical evidence for H1: Creative synthesis and star designers

We have shown empirically that collaborating with a star increases the likelihood of a focal designer becoming a star herself. In this section we provide some evidence that the main mechanism behind this effect is, as claimed in H1, the transfer of creative synthesis skills. Our argument for H1 rested on three claims: (i) stars have mastered creative synthesis; (ii) focal designers learn tacit knowledge about creative synthesis when collaborating with stars; and so (iii) focal designers are more likely to become stars themselves after collaborating with stars. Evidence in favor of claim (iii) followed from the testing described in Section 3.4. Here we provide some empirical evidence for claims (i) and (ii).

It is challenging to derive direct measures of creative synthesis or the transference of that skill set. Creative synthesis is a micro-level process, and it presupposes that collaborators have developed a deep understanding of the existing innovation paradigm and can create a new one by reconciling distant and often seemingly contradictory perspectives; such synthesis is produced by innovators who excel at focusing collective attention, enacting ideas, and building on similarities. Our data set does not allow for direct measurement of these micro processes. Yet we can measure a reliable indicator of an indispensable corollary of creative synthesis. That is, what makes creative synthesis unique is less the creation of breakthroughs through new-to-the-world combinations of knowledge fields and more how designers *follow up* after identifying a new-to-the-world combination. In a traditional "recombinatorial" approach to innovating, the innovators go on to devise new combinations with the expectation that one of them will become a breakthrough (Fleming 2001). In contrast, collaborators engaged in creative synthesis have identified a new paradigm based on the new combination; they are focused on producing exemplars of this new creative insight, and they continue to iterate and refine the new paradigm building upon its basic premise. Thus these collaborators will use the new combination repeatedly. It is most fortunate that our data set is rich enough to enable measurement of such *reuse*, by the focal designer, of new knowledge combinations that she created.

In order to operationalize the concepts of "new combinations" and "reuse of new combinations", we exploit the US Patent Office's sorting of all design patents into some 33 classes and hundreds of subclasses based on their subject matter. Many patents fall into more than one class or subclass. (The USPTO updates their classification periodically; we use the 2010 scheme.) We follow Fleming et al. (2007) and define as a *new combination* a pair of subclasses in a patent application that appears in the USPTO design patent database for the first time. Any further uses of this combination are treated as conventional combinations. In order to establish a baseline, we treat all subclass pairs through the end of 1984 as conventional combinations and start identifying new pairs in 1985 (which is the starting year of our empirical analysis). We say that a focal designer *reuses* a new combination if the designer has filed a patent with a new combination and then subsequently files other patents with the same subclass pair.

Do stars engage more than non-stars in creative synthesis? We estimate a logistic regression model to find whether stars are more likely than non-stars to *reuse* their new idea combinations. Since we are testing the likelihood that a designer reuses one of her own new combinations, the unit of analysis is the designer who has created a new combination—and who is observed each time she is granted a patent thereafter. Our dependent variable is a *Reuse* dummy set to 1 if the patent contains at least one reuse of a new combination previously created by the designer (and set to 0 otherwise). Our main independent variable is the indicator *Star*, which is set to 1 (resp., to 0) for individuals who are (resp., are not) a star.

As controls we use all variables defined for the previous matching analysis and for the tests of H1. However, our *Number of collaborators* variable now includes all collaborators (i.e., stars and non-stars) because in this analysis we must control for the focal designer's engagement in collaboration with others more generally. Correctly predicting the probability of new combinations being reused requires that we control also for the designers' number of past patents and the number of past new combinations.

Our regression results are given in Table 6. Model [1] limits the sample to patents without any collaborators (lone patents) and provides strong evidence that stars exhibit creative synthesis skills when working alone. Model [2] is based on a sample of patents for which the focal designer does not collaborate with a star. Model [3] contains all the patents considered for this analysis. For all three models, the *Star* dummy is both positive and significant ($p < 0.01$); this result indicates that stars are more likely than other innovators to reuse their own previously created new combinations. These models thus provide evidence that stars engage more than do non-stars in behaviors that are consistent with creative synthesis.

Table 6. Logit Regression on the Likelihood of Combination Reuse

Variable	[1] Lone patents		[2] No star collab patents		[3] All patents	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Star dummy	0.425***	(0.128)	0.300***	(0.109)	0.337***	(0.091)
Number of new combinations	0.011**	(0.004)	0.015***	(0.004)	0.015***	(0.003)
Number of patents	0.004*	(0.002)	0.006***	(0.002)	0.002*	(0.001)
Number of collaborators	-0.004	(0.013)	0.019***	(0.006)	0.011**	(0.005)
Number of citers	-0.001	(0.001)	-0.002***	(0.001)	-0.001**	(0.001)
Assignee's past patents	0.021	(0.024)	0.012	(0.017)	0.007	(0.016)
Class diversity	0.019	(0.02)	-0.004	(0.02)	-0.004	(0.017)
Mobility	-0.070**	(0.028)	-0.060**	(0.023)	-0.022	(0.016)
Location diversity	0.02	(0.041)	-0.003	(0.035)	-0.046	(0.033)
Patent stock year	-0.08	(0.05)	-0.044	(0.036)	-0.027	(0.033)
Cohort	yes		yes		yes	
Designers	32732		60285		64049	
Observations	48430		91525		103955	
Log likelihood	-8262		-16500		-19287	

Robust standard errors clustered by focal designers shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Do focal designers learn creative synthesis from star collaborators? Next we address the question of whether focal designers learn creative synthesis behavior by collaborating with stars. For this purpose, we assess the extent (if any) to which a focal designer is more likely to reuse new combinations after collaborating with a star.

For this analysis we define *Reuse probability* as the ratio of a focal designer's patents that contain a reused combination to the total number of patents that the designer has been granted. We test for reuse probability by designers—after their collaboration with a star—via a difference-in-differences (DID) analysis based on a CEM sample (Angrist and Pischke 2009). We employ the same CEM procedure described in Section 3.3 but with one modification: rather than creating matched pairs based on number of patents granted before the treatment, we match designers based on their respective reuse probabilities.

To construct a sample for the DID analysis, we observe all of the treated designers (those who collaborated with a star) and control designers for as many as 12 years (see Singh and Agrawal 2010). Deriving meaningful comparisons of pre- and post-treatment performance requires that both the pre- and post-treatment periods for all designers of interest be at least two years long.

Our DID sample for this analysis consists of 2,444 individuals, 1,222 each in the treatment and control groups. The values of our matching variables (not shown here for brevity) are not statistically distinguishable—between treatment and control group. Note that we include only those patents of the focal designer that are *not* made in collaboration with a star (except, of course, for the treatment event patent, which involves a star by definition). This approach makes it easier to isolate the learning effect from other effects of collaboration with a star, which is the treatment event.

As shown in the first row of Table 7, the reuse probabilities of these two groups are statistically indistinguishable *before* the treatment event of a star collaboration. However, there is a positive and significant boost (at the 0.05 level) in reuse probability among the treated designers following their star collaboration. Even as the reuse probability remained practically unchanged for the control group, it increased by a factor of nearly 8 for the treatment group.

We also perform these CEM and DID procedures for subsamples that contain (i) only patents held by lone inventors and (ii) all patents, including those resulting from star collaborations. Each subsample yields robust evidence that treated designers engage in more reuse combinations after collaborating with a star, although for case (i) the results are only marginally significant (at the 0.1 level). This outcome is not surprising in light of the very stringent selection of lone designer patents.

Table 7. Difference-in-Difference Analysis of Reuse Probability

	Treated group	Control group	Difference (Treated – Control)	LO95%	HI95%
Pre star-collaboration (n=8,874)	0.016	0.035	-0.019	-0.060	0.022
Post star-collaboration (n=18,010)	0.126	0.039	0.087	0.010	0.164

N=26,884 designer-year observations. To facilitate interpretations of the results all variables have been multiplied by 100.

In sum, our analyses offer evidence that stars engage in more creative synthesis than do non-stars and that designers can learn creative synthesis from their star collaborators. Despite some limitations of the measures employed, our analyses confirm that star collaborations increase the focal designer's likelihood of becoming a star by activating and transferring creative synthesis skills—a dynamic that echoes our main theoretical argument behind Hypothesis 1.

3.6. Testing the effects of network cohesion and expertise similarity

In this section we test Hypotheses 2 and 3 and show how collaborating with a star differs from collaborating with a non-star—as evidenced by the contrasting effects of network cohesion and expertise similarity. Because we posit distinct effects of network cohesion or expertise similarity on star versus non-star collaborations, we must use a sample that differs from the one used to test Hypothesis 1; in particular, we must focus on designers who have a non-star *and* a star collaborator in their network so that the network variables of interest can be measured for both star and non-star collaborations. This criterion selects 27,278 designer–patent observations in our 1985–2004 observation window.

The sample so selected includes designers who have collaborated with at least one star and one non-star collaborator, so the results from testing H2 and H3 must be interpreted as being *conditional* on designers collaborating with both stars and non-stars. Much as in the empirical challenge faced by Bode et al. (2015), this approach is a less aggressively causal interpretation—in line with a "treatment on the treated" view of these effects (Angrist and Pischke 2009).

A modest amount of notation helps us define the independent variables. Because the relative order of events will matter for our proposed event history analysis, we index each patent application date with $t \in [1, T]$;

here t is an integer and T is the last instance of a patent application in our data. In what follows, we use $\boldsymbol{H}_{it}$, $\boldsymbol{L}_{it}$, and $\boldsymbol{F}_{it}$ to denote the sets of (respectively) stars, non-stars, and all collaborators with whom focal designer i has worked until time t. Similarly, $\boldsymbol{G}_{jt}$ is the set of past collaborators of star j at time t.

Direct ties to collaborators. We retest the baseline H1 by measuring focal designer i's direct ties to stars and to non-stars as a count of the number of her unique star collaborators until time t (denoted $|\boldsymbol{H}_{it}|$) and unique non-star collaborators until time t ($|\boldsymbol{L}_{it}|$), respectively.

Network cohesion. Testing H2 requires that we measure the (social) network cohesion of the focal designer i at time t with respect to her star ($\boldsymbol{H}_{it}$) and non-star ($\boldsymbol{L}_{it}$) collaborators. Our cohesion measure captures the average fraction of common third parties within the focal designer's network. This measure is equivalent to that actor's local network density, which is defined as the ratio of existing ties in her network to all possible ties (Fleming et al. 2007, Gargiulo et al. 2009, Obstfeld 2005). For our study, network cohesion must be defined with respect to two types of collaborators: stars and non-stars. Based on the general definition, we therefore assess the focal designer i's network cohesion with respect to her star collaborators by calculating the (average) proportion of her past collaborators who also collaborated with her star collaborators ($j \in \boldsymbol{H}_{it}$). Formally, we have

$$Network\ cohesion\ with\ stars_{it} = \frac{\sum_{j \in \boldsymbol{H}_{it}} (|\boldsymbol{G}_{jt} \cap \boldsymbol{F}_{it}| / |\boldsymbol{F}_{it}|)}{|\boldsymbol{H}_{it}|},$$

which gives the average fraction, in the focal designer's network, of common third parties with a star collaborator. The resulting continuous measure is equal to 0 if there are *no* third parties in common with any star in the focal designer's network and is equal to 1 if *all* the focal designer's past collaborators are also past collaborators of her star collaborators. We define *Network cohesion with non-stars* analogously.

Expertise similarity. In order to identify—for any moment in time—the areas of expertise of the designers in our database, we rely on the classification of design patents made by the USPTO. Designs in the USPTO patent classes (and their subclasses) pertain to a "specific type of industrial design" and require substantially different skill sets to produce. It is therefore reasonable to view each subclass as a distinct area of expertise.

Following previous work that measures knowledge overlaps between actors (Reagans 2005, Reagans and McEvily 2003, Sosa 2011), we measure *Expertise similarity with stars* as the (average) fraction of areas of expertise that are common, to both the focal designer $\boldsymbol{i}$ and a star collaborator $\boldsymbol{j}$, divided by the number of the focal designer's areas of expertise. Let $\boldsymbol{K_{it}}$ (resp. $\boldsymbol{K_{jt}}$) be the set of subclasses in which the focal designer $\boldsymbol{i}$ (resp., the star $\boldsymbol{j}$, $\boldsymbol{j} \in \boldsymbol{H_{it}}$) has been granted patents until time $\boldsymbol{t}$. Then

$$\boldsymbol{Expertise\ overlap\ with\ stars_{it}} = \frac{\sum_{j \in \boldsymbol{H_{it}}} (|\boldsymbol{K_{it}} \cap \boldsymbol{K_{jt}}| / |\boldsymbol{K_{it}}|)}{|\boldsymbol{H_{it}}|}.$$

This variable, too, ranges from 0 to 1; here 0 indicates no expertise similarity between the focal designer and all her star collaborators and, at the other extreme, 1 indicates a complete overlap between the parties' areas of expertise. We analogously define *Expertise similarity with non-stars*.

In order to identify the different effects that star and non-star collaborators have on network cohesion and expertise similarity, we must control not only for the focal designer's characteristics but also for those of her star and non-star collaborators. So in addition to the control variables used to test H1, we include three sets of control variables defined with respect to both star and non-star collaborators; see Table 8.

Table 8. Definition of Variables for Testing H2 and H3

Star's citers. As a control for the social attention that collaborating with a star may bring to the focal designer's work, we define the *Star's citers* as the number of individuals who have, up to time *t*, cited the star's patents. We may suppose that a star whose patents are cited by more designers has accumulated more social attention. A star with a larger following can bestow more social attention on collaborators than can a star with a smaller following. *Non-star's citers* is defined analogously.
Star's direct ties. This variable captures the network size of all of the stars with which a focal designer i has worked up to time t. We define $Star's\ direct\ ties_{it} = \left|\bigcup_{j \in \boldsymbol{H}_{it}} \boldsymbol{G}_{jt}\right|$. Since collaboration consumes time and energy, stars with more collaborators might offer fewer benefits (on average) to the focal designer. We define *Non-star's direct ties* similarly.
Repeated collaborations with stars. To control for the closeness between the focal designer and her collaborators, we adopt a strength-of-tie measure based on observations of repeated collaborations (Fleming et al. 2007, Hansen 1999, McFayden and Cannella 2004). Our variable measures a focal designer's tendency to

collaborate repeatedly with the same star(s). Formally, with $c_{ijt_0} = 1$ if designers i and j collaborate at time t_0 and with $c_{ijt_0} = 0$ otherwise. We define $Repeated\ collaborations\ with\ stars_{it} = (\sum_{t_0=1}^{t-1} \sum_{j \in \boldsymbol{H}_{it}} c_{ijt_0}) / |\boldsymbol{H}_{it}|$. The value of this measure is 1 when the focal designer collaborates with a given star exactly once; the value increases when that focal designer works with the same star on subsequent projects. We measure *Repeated collaborations with non-stars* equivalently.

Table 9 gives summary statistics and correlations for all our defined variables. Table 10 reports our results from the event history analysis used to test H2 and H3. Model [1] includes all the control variables. Model [2] is a partial model that includes the effects of the focal designer's number of non-star and star collaborators. Model [3] includes our network cohesion variables, and Model 4 includes the expertise similarity variables. Model [5] is the full model, which we shall use to test all our hypotheses and then to interpret the results.

Before testing our hypotheses, the effects of one set of controls are noteworthy. We specifically control for collaborators' prominence in the field by measuring the number of other designers who have cited their work. The effects of these variables (for both star and non-star collaborations) are positive and highly significant, which suggests that the attention from other designers (the collaborators' citers) that the focal designer's collaborators attract do have a positive impact on the star emergence of the focal designer. Since stars have (on average) an order of magnitude more citers, focal designers benefit more when collaborating with stars. In addition, because our *Star's citers* and *Non-star's citers* are proxies of the attention pool that a focal designer gets from her collaborators (and by definition from their common third parties), these controls effectively account for the contribution to star emergence of the possible increased attention that working with a prominent star might bring to a focal designer.

Before testing H2 and H3, we retest H1 with the sample used to test H2 and H3. The coefficients for *Direct ties to non-stars* (0.426, $p < .01$) and for *Direct ties to stars* (0.673, $p < .01$) are positive and also significant. More importantly, the difference between these two collaboration effects is statistically significant ($p < .017$). It is clear that these sample data also support our baseline hypothesis that a star collaboration is significantly more beneficial than a non-star collaboration—that is, even for the sample of designers who have collaborated at least once with both a star and a non-star.

Table 9. Summary Statistics and Correlations for All Variables

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	*Direct ties to non-stars (ln)*	1.59	0.66	1.00															
2	*Direct ties to stars (ln)*	0.91	0.33	0.27	1.00														
3	*Social cohesion with non-stars*	0.47	0.24	-0.06	-0.06	1.00													
4	*Social cohesion with stars*	0.51	0.26	0.03	0.02	0.83	1.00												
5	*Expertise overlap with non-stars*	0.63	0.31	-0.42	-0.26	0.65	0.51	1.00											
6	*Expertise overlap with stars*	0.73	0.29	-0.37	-0.19	0.57	0.58	0.77	1.00										
7	*Non-stars citers (ln)*	2.05	1.96	0.46	0.35	-0.17	-0.07	-0.34	-0.24	1.00									
8	*Stars' citers (ln)*	4.81	1.11	0.24	0.55	-0.04	0.00	-0.22	-0.17	0.26	1.00								
9	*Non-stars' direct ties (ln)*	2.19	0.90	0.66	0.39	-0.03	0.06	-0.30	-0.28	0.69	0.38	1.00							
10	*stars' direct ties (ln)*	2.89	0.86	0.43	0.52	0.15	0.24	-0.11	-0.08	0.28	0.69	0.56	1.00						
11	*Repeated collaboration with stars*	2.05	2.18	0.04	0.07	0.08	0.08	0.05	0.04	0.10	0.02	0.02	-0.04	1.00					
12	*Repeated collaboration with non-stars*	2.42	2.88	0.08	0.12	0.01	0.13	-0.11	0.10	0.12	0.09	0.04	0.01	0.71	1.00				
13	*Assignee's past patents (ln)*	3.95	1.95	-0.01	0.21	-0.08	-0.05	-0.08	-0.04	0.16	0.26	0.13	0.16	0.03	0.04	1.00			
14	*Class diversity*	3.47	2.99	0.38	0.29	-0.45	-0.35	-0.71	-0.56	0.35	0.19	0.29	0.09	0.23	0.34	0.07	1.00		
15	*Mobility*	1.50	1.10	0.36	0.12	-0.33	-0.29	-0.45	-0.46	0.22	0.11	0.27	0.11	-0.01	0.03	-0.23	0.47	1.00	
16	*Location diversity*	1.05	0.25	0.10	0.05	-0.14	-0.12	-0.18	-0.17	0.07	0.05	0.07	0.03	-0.01	0.01	0.02	0.14	0.14	1.00
17	*Patent stock year (ln)*	6.67	0.72	0.10	0.10	0.01	0.02	-0.08	-0.05	0.13	0.27	0.17	0.20	0.01	0.03	0.08	0.08	0.00	0.02

N=27,278. Correlations greater than |0.012| are significant at $p < 0.05$

The results from testing H2 confirm that increased network cohesion has a negative (resp. positive) effect on the outcomes of collaborations with non-star (resp. star) designers. Model [5] strongly supports both H2a and H2b. The negative and significant coefficient for *Network cohesion with non-stars* (-1.650, $p < .01$) indicates that having a more cohesive social network with a non-star collaborator reduces, on average, the likelihood of becoming a star—in line with H2a. Thus an increase of one standard deviation in the value of *Network cohesion with non-stars* makes the focal designer's likelihood of emerging as a star 33% less likely ($e^{(-1.650\times0.24)} - 1 = -0.33$). In contrast, the positive and significant coefficient for *Network cohesion with stars* (0.371, $p < .05$) indicates that having a more cohesive social network with a star collaborator increases, on average, the focal designer's likelihood of becoming a star; this result accords with H2b. Indeed, an increase of one standard deviation in the value of *Network cohesion with stars* is associated with a 10% increase ($e^{(0.371\times0.26)} - 1 = 0.10$) in the likelihood of the focal designer becoming a star.

Table 10. Proportional Hazard Model Predicting Star Emergence for Testing H2&H3

Variable	[1]	[2]	[3]	[4]	[5]
Direct ties to non-stars (H1)		0.496***	0.339***	0.506***	0.426***
		(0.049)	(0.048)	(0.05)	(0.051)
Direct ties to stars (H1)		0.502***	0.594***	0.654***	0.673***
		(0.108)	(0.094)	(0.092)	(0.089)
Network cohesion with non-stars (H2a)			-1.715***		-1.650***
			(0.166)		(0.205)
Network cohesion with stars (H2b)			0.394***		0.371**
			(0.123)		(0.168)
Expertise sim. with non-stars (H3a)				-2.145***	-1.032***
				(0.213)	(0.161)
Expertise similarity with stars (H3b)				0.555***	0.469***
				(0.17)	(0.131)
Controls					
Non-stars' citers	0.370***	0.349***	0.319***	0.324***	0.311***
	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)
Stars' citers	0.269***	0.262***	0.165***	0.175***	0.153***
	(0.035)	(0.04)	(0.037)	(0.038)	(0.038)
Non-stars' direct ties	-0.243***	-0.423***	-0.386***	-0.405***	-0.377***
	(0.041)	(0.043)	(0.043)	(0.044)	(0.044)
Stars' direct ties	-0.288***	-0.448***	-0.359***	-0.343***	-0.333***
	(0.045)	(0.045)	(0.044)	(0.046)	(0.045)
Repeated collaboration with non-stars	0.082***	0.091***	0.124***	0.090***	0.114***
	(0.02)	(0.02)	(0.02)	(0.017)	(0.018)
Repeated collaboration with stars	-0.019	-0.024	-0.036*	-0.008	-0.025
	(0.02)	(0.02)	(0.019)	(0.016)	(0.016)
Assignee's past patents	0.115***	0.130***	0.127***	0.114***	0.116***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Class diversity	0.198***	0.174***	0.128***	0.143***	0.127***
	(0.01)	(0.01)	(0.012)	(0.01)	(0.011)
Mobility	0.072**	0.056**	0.048**	0.019	0.028
	(0.029)	(0.028)	(0.024)	(0.025)	(0.024)
Location diversity	0.119	0.084	0.006	0.029	0.007
	(0.092)	(0.092)	(0.086)	(0.089)	(0.087)
Patent stock year	0.153***	0.164***	0.135***	0.160***	0.145***
	(0.037)	(0.036)	(0.036)	(0.037)	(0.037)
Cohort	Yes	Yes	Yes	Yes	Yes
Log likelihood	-20786	-20701	-20579	-20538	-20509

N=27,278 designer-patent observations; 11,573 designers. Robust standard errors clustered by focal designer are reported in parentheses. All models control for cohort dummy variables. **p* < 0.10, ***p* < 0.05, ****p* < 0.01

Hypothesis 3 proposes that greater expertise similarity with a non-star (resp. star) collaborator decreases (resp. increases) the focal designer's odds of emerging as a star. Our regression results strongly support H3. The negative and significant coefficient for *Expertise similarity with non-stars* (−1.032, $p < .01$) indicates that designers who have greater expertise similarity with such non-star collaborators thereby reduce significantly their likelihood of becoming a star, in line with H3a. Here an increase of one standard deviation in *Expertise similarity with non-stars* reduces the likelihood of emergence as a star by 27% ($e^{(-1.032\times0.31)} - 1$

= −0.27). In contrast, the positive and significant coefficient for *Expertise similarity with stars* (0.469, $p < .01$) indicates that designers who collaborate with stars increase their likelihood of becoming a star by increasing their expertise similarity with star collaborators—in line with H3b. An increase of one standard deviation in *Expertise similarity with stars* increases the probability of becoming a star by 15% ($e^{(0.469\times0.29)} - 1 = 0.15$).

The contrasting effects (for star vs. non-star collaborations) associated with both network cohesion and expertise similarity provide additional evidence that star and non-star collaboration are different and are characterized by different mechanisms. More specifically: in non-star collaborations, the focal designer benefits much more from open social structures and access to diverse sources of information, which can spark the generation of divergent ideas; in star collaborations, more cohesive social structures and the opportunity for greater absorptive capacity with the star collaborator provide the supporting conditions to experience and learn creative synthesis.

4. DISCUSSION AND CONCLUSION

Even though past research has recognized the importance of stars as collaborators, we have only a limited understanding of how the creative aspects of collaborating with stars differ from those of collaborating with non-stars—and, as a consequence, of how star collaborations affect the emergence of future stars (Azoulay et al. 2010, Groysberg and Lee 2009, Oettl 2012). Our paper addresses this gap in the literature by building a theory of how the creative aspects of collaborating with stars differ from their non-star collaboration counterparts; we do this by showing that such differences result in a higher likelihood of star emergence and by identifying the conditions under which collaborating with creative stars is most effective. Our findings have a number of implications as this paper contributes to the literature on creativity management and interpersonal collaboration.

The literature on creativity has long wondered whether individual creativity (i.e., the ability to produce novel and useful work) is "contagious" (McFayden and Cannella 2004, Perry-Smith and Shalley 2003). Our paper shows that it may very well be. We observe that individual creativity is enhanced not only by an innovator collaborating with others to access diverse information sources of information but also, and more lastingly, by collaborating with others to learn creative synthesis skills. We argue that such a transfer of skills is more likely to occur when a focal innovator collaborates with creative stars.

This theory, and its supporting empirical evidence, also identifies a previously unreported link between the emerging field of creative synthesis within the creativity literature (Chen and Adamson 2015, Harvey 2014, 2015) and the extant literature on interpersonal collaboration. We show how interpersonal collaboration is the conduit for transmitting knowledge about creative synthesis. Absent such a pathway, one must assume that creative synthesis skills emerge spontaneously and are discovered independently by different innovators. Having identified star collaborations as a conduit for the transmission of creative synthesis skills, we see more systematic patterns in the emergence of such skills. We remark that a star-driven emergence and dissemination of creative synthesis skills is consistent with anecdotal evidence that organizations known to employ effective creative synthesis approaches have, indeed, been led by creative stars. Examples include John Lasseter at Pixar Animation Studios and Ferran Adrià at the former El Bulli, a top-rated restaurant serving vanguard cuisine; these creative individuals put creative synthesis into action and helped others develop their own creative synthesis skills (Svejenova et al. 2007, Catmull and Wallace 2014).

Our work speaks directly and primarily to the literature on interpersonal collaboration in creative settings by challenging the widely held assumption that there is no need to differentiate collaborators in terms of quality—in other words, that collaboration is most accurately viewed as a homogeneous construct. However, identifying the *sources* of collaborators' observed heterogeneity is necessary in order to advance our understanding of how social network mechanisms actually operate. For example, McEvily et al. (2012) use seniority as a source of heterogeneity in collaborative relationships and find that lawyers benefit primarily from the collaborative ties, established at the beginning of their careers, with senior lawyers. Our work advances the social network literature by establishing that variation in collaborators' relevant characteristics (i.e., their respective quality) has significant effects that merit more systematic study. Consider, for example, our findings that social and knowledge network constructs (viz., social network cohesion and expertise similarity) affect star emergence contingent upon the collaborator's quality. Both of these constructs benefit the innovator collaborating with a star because they create an environment ideally suited to the practice of creative synthesis and the transfer of those skills; yet such cohesion and similarity are detrimental to the innovator collaborating with a non-star because they limit access to diverse sources of information. These contrasting results call for scholars to exhibit caution when tempted to view either social or knowledge structures as homogenous. Our research demonstrates that, at least in creative settings, the quality of collaborators matters significantly and should therefore be taken into account, both theoretically and empirically, when studying collaborative knowledge networks.

We argue along similar lines that these contrasting effects reveal a logical connection between two streams of the interpersonal collaboration literature that have heretofore developed separately and have often been construed as advancing opposed messages. Our findings on the role of both social network cohesion and expertise similarity as facilitators in the transfer of creative synthesis skills in star collaborations is entirely consistent with previous work studying knowledge transfer from the source to the recipient (Reagans and McEvily 2003) and on the assimilation of cross-boundary knowledge that would otherwise be difficult for the recipient to acquire (Tortoriello and Krackhardt 2010, Tortoriello et al. 2012). At the same time, our work is consistent with the literature that focuses on the idea generation aspects of collaboration. The detrimental effects of social network cohesion and expertise similarity on star emergence in a non-star collaboration mirror previous work, which has documented that exchanges in open (as compared with closed) social network structures are more likely to generate potentially creative ideas (Burt 2004, Fleming et al. 2007), as are more exchanges of diverse information (Rodan and Galunic 2004, Sosa 2011). We can reconcile these seemingly contradictory effects by pointing to collaborator quality as the factor that determines which account is more applicable. Hence we can offer practical guidelines for when researchers and practitioners should apply each theory.

From an empirical standpoint, examining the effects of interpersonal collaboration is a daunting exercise. There is one issue in particular, however, that warrants further discussion. Recall that social attention mechanisms definitely factor into an innovator's emergence as a star following collaboration with a star. We therefore faced the empirical challenge of providing evidence for the transfer of creative synthesis skills—from the star to the focal designer—above and beyond any social attention mechanisms. We address that challenge by way of three different approaches. First, we introduce a control for the increased social attention to which a star exposes a focal innovator. We find, as expected, that the social attention resulting from both star and non-star collaborators plays an important role in the focal innovator's emergence as a star; however, it does not fully explain the observed variation in the probability of becoming a star. Second, we suppose that different creative mechanisms are triggered by collaborators of different quality (here, stars vs. non-stars). Indeed, we report empirical evidence that an innovator exhibits a significant behavioral change that is consistent with having learned the stars' mechanism after having collaborated with a star—a behavioral change that is *not* observed when the focal innovator collaborates with a non-star. More specifically: by tracking the reuse of new class combinations in the design patent database, we discover that star designers are more likely than non-stars to reuse novel ideas—an indication that star designers dwell longer on making refinements to an initial invention and also construct more exemplars of a new paradigm (Harvey 2014). We then use a DID approach to show that a focal designer who collaborates with a star (rather than a non-star) is more likely to emulate "star" behavior, as evidenced by a significant increase in the tendency of such designers to reuse their previously created novel combinations. (Employing a DID framework, we also confirmed that a focal designer significantly increases her patenting productivity after collaborating with a star—in line with the within-dyad mechanisms driving our hypotheses.) Third, on a conceptual level our contingencies are somewhat more consistent with a knowledge-sharing mechanism than with an attention transfer mechanism. We know that expertise similarity improves the learning environment (and thus enables knowledge sharing) but also hinders access to the diverse information needed to generate novel ideas. However, it is theoretically unclear how expertise similarity would be associated with the transfer of social attention.

An important caveat to this study concerns its reliance on archival data derived from design patents, an approach that entails several constraints common to all research based on patent activity. For example, our findings are based solely on successful collaborations—that is, those resulting in a patent (or patents) being granted. Yet it is also possible, of course, for designer–star collaborations to fail. Because our paper focuses on how collaboration affects exceptional outcomes (i.e., becoming a star), our conclusions should not be invalidated by our not having data related to failures. As usual, fully establishing causality in archival data is complicated by the possibility of unobserved characteristics driving both the exposure to and the outcome of the "treatment" (becoming a star). Although the nature of our data is not such that all doubt can be removed, our robustness checks provide evidence that our results should not be viewed as spurious.

In reviewing the lives of eminent philosophers from ancient China and Greece, Collins (1998) found that philosophers of comparable creative eminence tend to appear in the same generation. There is anecdotal evidence from historians and sociologists that great figures, early in their careers, studied under prominent individuals of their era. Our paper is the first one that employs an extensive design patent data set as a means to quantify the effects of collaborating with a star designer and thereby help explain the phenomenon of star emergence. A unique aspect of this study is our finding that knowledge transfer in such collaborations is strongly affected by the quality of collaborators. A firm could use these results when seeking to improve its cultivation of future stars; doing so should increase its design competitiveness and could well lead to beneficial changes in the firm's focus and direction.

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