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

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Despite being rare, stars make disproportionately influential contributions to their fields. This paper studies the role of inter-personal collaboration in the emergence of star designers—in particular, how a designer's likelihood of becoming a star is affected by collaborating with stars as compared to non-stars. We find that collaborating with a star makes a designer much more likely to attain star status than collaborating with non-stars. More importantly, we examine how the quality of a collaborator (star vs. non-star) moderates the influence of two important contextual factors of collaboration: social network cohesion and expertise similarity. Social network cohesion and expertise similarity have been associated with both positive and negative collaboration outcomes in prior literature. By distinguishing collaborators based on their quality, we reconcile those contrasting results. We test our predictions on a large longitudinal data set consisting of all designers who were granted a design patent in the United States from 1975 through 2010.

Keywords: Star; Inter-personal Collaboration Networks; Emergence of Stars; Design Patents; Knowledge Transfer

1. INTRODUCTION

Design capabilities have become crucial for companies as they seek to gain a competitive advantage (Brown 2008, Xia et al. 2015). Hence the designer's role has evolved from focusing solely on the aesthetic to addressing more consequential concerns, such as establishing product concepts and even defining product strategies (Ulrich 2011a, Verganti 2010). "Star" designers have become celebrities in their own right (Godart et al. 2015, Miller 2013) for whom firms increasingly compete: Apple hired the Australian designer Marc Newson in 2014 ahead of its "AppleWatch" launch; eBay hired John Maeda, former president of the Rhode Island School of Design; and Adidas attracted three prominent Nike footwear designers Denis Dekovic, Marc Dolce and Mark Miner as part of its plan to open a "Brooklyn Creative Studio" in New York City.

The role of stars has been studied in various contexts (Azoulay et al. 2010, Ernst et al. 2000, Groysberg and Lee 2009, Hess and Rothaermel 2011, Oettl 2012, Zucker et al. 1998). The contributions of stars to their respective fields are vastly disproportionate (Ernst et al. 2000) and so, in a business context, stars are of considerable value to their employers (Godart et al. 2015, Groysberg and Lee 2009, Zucker et al. 1998). However, we still have a limited understanding of whether and how stars affect collaboration outcomes and, in particular, little knowledge about their impact on the subsequent careers of their collaborators. Does collaborating with a star designer affect the focal designer's emergence as a star later in her career? More importantly, how do star collaborations (i.e., those in which a focal designer works with, at least, one star designer) differ from non-star collaborations? These are the questions that this paper addresses.

The benefits of interpersonal collaboration in creative settings have been well documented in terms of both the collaboration outcomes (Uzzi and Spiro 2005, Wuchty et al. 2007) and the collaborators' career advancement (Fleming, Mingo, et al. 2007; Azoulay et al. 2010; Tortoriello et al. 2015). However, previous research has not distinguished between different types of collaborators—in particular, between star and non-star collaborators. Yet distinguishing collaborators based on their quality is crucial for two reasons. First, given the prominence of and disproportionate contributions to their fields made by stars, the question arises of whether collaborating with a star yields benefits for the focal collaborator that are likewise disproportionate. Second, and perhaps even more importantly, distinguishing collaborator types in terms of their quality is an intriguing yet unexplored opportunity to deepen our understanding of how interpersonal collaborations benefit or hinder collaborators.

One could argue that collaboration with a star is disproportionately beneficial to the focal collaborator because stars have, by definition, accumulated a disproportionately large amount of tacit design knowledge over their careers—not only about the designs themselves but also about the design process (Liedtka 2014). Indeed, stars have usually mastered knowledge, especially tacit knowledge, which most non-stars lack. When collaborating with a star, the focal designer is exposed to the star's tacit (design) knowledge, which would otherwise be difficult to access and assimilate (Reagans and McEvily 2003, Sosa 2011, 2014, Tortoriello et al. 2012, 2015). It follows that there is more potential for knowledge transfer through a star collaboration than through a non-star collaboration.

With regard to the differences between star and non-star collaborations, we focus on two of the most widely studied aspects of interpersonal collaboration and knowledge transfer (Gargiulo et al. 2009, Reagans and McEvily 2003, Reagans et al. 2015, Tortoriello et al. 2015) : *network cohesion*, or the extent to which two collaborators share the same third-party collaborators; and *expertise similarity*, or the extent to which two collaborators share similar past work-related experiences. On the one hand, both of these factors facilitate knowledge transfer because a cohesive network around a dyadic relationship builds the trust and cooperative behavior that "enforces" an effective knowledge transfer relationship while shared expertise establishes a common knowledge base and hence absorptive capacity (Cohen and Levinthal 1990, Reagans and McEvily 2003, Obstfeld 2005, Hargadon and Bechy 2006, Sosa 2011). On the other hand, excessive network cohesion and expertise similarity are often detrimental to creativity in that the former can cause social pressure that steers the group around the collaborative dyad to converge to "group think" and the latter implies a lack of the creative tension that would stem from collaborators who had different perspectives (Fleming, Mingo, et al. 2007, Janis 1972, Perry-Smith and Shalley 2003, Sosa

2011). We argue that network cohesion and expertise similarity will probably benefit a star collaboration because the sizable knowledge differential between the focal designer and the star collaborator heightens the importance of effective knowledge transfer. In contrast, in a non-star collaboration both factors are not beneficial because instead their detrimental effects on creativity predominate.

By answering the questions of *whether* and *how* a focal designer benefits more from a star than a non-star collaboration, we contribute to two streams of literature. First, distinguishing collaborators by their quality reveals an important contingency in interpersonal collaborations that helps to reconcile the extant literature's contrasting findings of effects associated with the roles of social and knowledge network structures. Second, by examining how collaboration with a star lead to the emergence of new stars, this paper contributes to the star performance literature and thereby yields insights into the genesis of outstanding creative performance.

We find support for our theoretical arguments in the empirical setting of industrial design. Our data on this industry come from the *design* patent database of the US Patent and Trademark Office (USPTO 2015)—in contrast with previous studies, most of which have focused on *utility* patents. Under US patent law, utility patents and design patents are two distinct legal entities: the former protects how an item works whereas the latter protects how an item looks. We processed design patent data for the period 1975–2010 to examine the careers of individual designers. From a pool of 144,288 designers who had been granted at least one design patent we identified 9,971 star designers based on their (design) inventions and influence.

2. DEVELOPMENT OF HYPOTHESES

In order to develop our arguments concerning how different kinds of collaborators affect the focal designer's emergence as a star, we start by establishing a baseline hypothesis that lays out the fundamental differences between collaboration with a star designer and collaboration with non-stars.

The notion of *tacit knowledge transfer* is crucial to our hypotheses development because much of design knowledge is tacit (Hargadon and Bechy 2006, Rindova and Petkova 2007, Verganti 2010). We remark that good (industrial) design is characterized by a feel for the avant-garde, a unique approach to the development of form and styles, an appreciation of beauty, and a talent for visualization as well as a deep understanding of material, color, texture, and space (Lidwell et al. 2010). Furthermore, the design process itself is far from linear and deterministic; it lacks a definitive formulation and solutions are highly uncertain (Brown 2008, Dougherty 1992, Ulrich and Eppinger 2015). As a result, linear and/or analytical design approaches seldom yield satisfactory results. A good designer must therefore be skilled in experimental approaches that investigate multiple and possibly competing potential solutions (Becham and Barry 2007, Loch et al. 2001). Hence it is clear that tacit knowledge figures prominently in what constitutes a good design and in how a good design process evolves; however, such knowledge is difficult to articulate and is "inseparable from action because it is constituted through such action" (Orlikowski 2002, p. 251).

Star designers possess an incomparable mastery of their respective fields. They have developed an extensive realm of information that far exceeds the average designer's knowledge. Stars are accorded higher recognition not only because of their extraordinary skills but also because of the quality (and uniqueness) of their attained knowledge (Galunic et al. 2012). Because design knowledge is largely tacit, it cannot be codified and is difficult to articulate. Hence this knowledge is not easily transferred (Zander and Kogut 1995) and can truly be acquired only through experience (Nelson & Winter, 1982; von Hippel, 1994). Scholars have therefore argued that collaboration, up-close observation, and emulation are the main mechanisms by which tacit knowledge is transferred (Nonaka 1994, Orlikowski 2002). It follows that, for a relatively inexperienced designer, collaboration with a star is a viable way—and perhaps the only effective way—to tap into the star's superior design knowledge.

Given the considerable difference in the knowledge of a star versus a (non-star) focal designer, interpersonal collaboration becomes the conduit through which knowledge can flow from star to focal designer. The latter gains access to the former's knowledge stock through their close collaboration on a project. That interaction provides opportunities for an intense exchange of knowledge, ideas, and techniques shaping the focal designer's way of thinking. In comparison, the knowledge differential between the focal designer and a non-star collaborator is much less pronounced; some knowledge may be exchanged, but the collaborators spend less time transferring knowledge than experimenting and jointly exploring the solution space. So to the extent that knowledge flows bear on the focal designer's own emergence as a star, collaboration with a star should have a far greater effect than collaboration with a non-star.[1] We formalize these considerations in a first hypothesis.

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

Although there is a well-established literature on the benefits of interpersonal collaboration in various settings, including creative ones, that literature has not explicitly distinguished collaborators based on their quality; instead, collaboration is typically viewed as a homogeneous construct. To the best of our knowledge, the work that comes closest to acknowledging the influence of collaborator quality on collaboration outcomes is Waldinger (2010). However, he studies how the quality of a university department affects PhD student prospects and therefore also considers factors beyond interpersonal collaboration (e.g., the training program and teaching requirements). Furthermore, that work focuses on the negative effects of interrupting a collaboration rather than the positive effects of initiating collaboration.

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[1] Another mechanism that could explain the differences between star and non-star collaborations is *status transfer* from the star designer to her collaborators (Simcoe and Waguespack 2011), which may (or may not) be uncorrelated with knowledge transfer. Other designers could view the focal designer as more capable simply because of that person's association with a star. In this case, a star's association lends public credibility to the focal designer because a star's endorsement carries more weight in the community than would the endorsements of non-star individuals (Stewart 2005). It is probable that the status transfer mechanism is largely independent of the mechanism for transferring tacit knowledge, so we do not discuss the former from a theoretical viewpoint. However, we control for it in our hypotheses testing.

It is intuitive to suppose that better collaborators will result in better collaboration outcomes. Less intuitive, however, is identifying how a quality difference in collaborators moderates the effects of factors that may ease or hinder knowledge transfer in inter-personal collaborations. Explanations of successful knowledge transfer and thus of outstanding creative performance, as postulated by Hypothesis 1, often emphasize the importance of two important contextual factors: (social) network cohesion and expertise similarity or overlap (Reagans and McEvily 2003, Sosa 2011, Tortoriello and Krackhardt 2010, Tortoriello et al. 2015). These factors are distinct, yet complementary, in that they emphasize (respectively) the social and knowledge aspects of dyadic interactions in collaboration networks (Reagans et al. 2015).

Network cohesion

If social network cohesion is high, then a large proportion of the focal designer's collaborators also collaborate with each other. In such cases, the focal designer augments her collaborator connections via common third parties. However, if social cohesion is low then the focal designer and her collaborators have been working mostly with different people that are not connected among themselves; in this case, the network will have many "structural holes" (Burt 1992) around the focal designer.

Network cohesion has been studied extensively in the literature, and two divergent effects have been postulated. On the one hand, cohesion induces trust in a social group (Coleman 1988); it thus increases the frequency of information exchange (Erickson 1998) and encourages cooperative behavior among collaborators (Coleman 1990, Obstfeld 2005, Hargadon and Bechky 2006, Helfat and Raubitschek 2000, Reagans and McEvily 2003, Uzzi 1997). Network cohesion ultimately increases the amount of knowledge transferred between collaborators (Amabile et al. 2005, Milliken et al. 2003), and encourages risk sharing (Granovetter 1985, Sosa 2011, 2014). A cohesive network has the further advantage of conveying a clear normative order within which the individual can experience a sense of direction—in contrast to a diverse or disconnected network, which exposes the individual to conflicting preferences and allegiances (Coleman 1988). Hence a cohesive network's members begin to resemble one another in terms of their thoughts, actions, and/or knowledge (Carpenter 2002), and these commonalities facilitate the transfer of tacit knowledge (Hansen 1999, Reagans and McEvily 2003, Uzzi and Spiro 2005).

That being said, a highly cohesive social network could have a negative effect on the focal designer's creativity. A cohesive network implies a denser group of collaborators and a higher percentage of redundant contacts, which results in fewer opportunities for the focal designer to broker ideas (Burt 2004, Hargadon and Sutton 1997). As the underlying differences between collaborators diminish, the social group becomes enamored of the status quo and the majority rule (Menon and Phillips 2011); "group thinking" sets in (Janis 1972). The social pressure for group conformance "traps" the focal designer and so limits her ability to think and act differently (Gargiulo and Benassi 2000). In contrast, a less cohesive network leads to opportunities for divergent thinking and stimulates different approaches to problem solving; the result can be ideas that are more creative (Fleming, Mingo, et al. 2007; Perry-Smith & Shalley 2003; Burt 2004, Sosa 2011). In a sparse social network, the focal designer is connected to collaborators who are not interconnected and hence is more likely to think independently, since there is no coherent group imposing its views.

The quality of the collaborator affects the balance between these countervailing effects of network cohesion. A star collaboration under high network cohesion improves the focal designer's odds of attaining star status herself—owing to the considerable difference between the star's and the focal designer's knowledge. It is therefore extremely important to have an effective conduit for the transfer of tacit knowledge (Boland and Tenkasi 1995). The star's social group may serve as that conduit because its members can be expected to adopt the star's norms, tastes, and behaviors. Thus the star collaboration proceeds in an environment that provides a consistent set of standards for the focal designer to assimilate (Galunic et al. 2012, Gargiulo et al. 2009). In addition, high levels of network cohesion increase the chances that an star acts more cooperatively to avoid spreading a negative reputation among his/her collaborators (Coleman 1990, Helfat and Raubitschek 2000, Reagans and McEvily 2003). The possibility remains that a cohesive network will induce its characteristic negative effect: reduced freedom to think in divergent ways. However, the efficiency of knowledge flows stemming from large differences (between star and focal designer) in design knowledge trumps the limits associated with a cohesive network structure.

That balance is reversed for a non-star collaboration. On average, non-stars are similar to the focal designer with regard to experience, behavior, and mastery of design knowledge. Hence the design knowledge differential in such collaborations is minor, which limits the focal designer's opportunity to acquire the tacit design knowledge necessary for developing extreme levels of creativity. Note also that, in light of the design process's highly uncertain nature, a cohesive set of designers with only an average understanding of their domain's knowledge base may lack the benefits of a (star) leader which they can learn from in an effective way. In the absence of a knowledge difference between the focal designer and her non-star collaborators, the positive effects of a cohesive network diminish even as its negative effects continue unabated. In short: within non-star collaborations, the negative effects of network cohesion dominate its positive effects.

Given that social network cohesion can affect star emergence in opposite ways depending on the collaborator's quality, we posit the following two-part hypothesis.

Hypothesis 2 **(H2).** *The focal designer's emergence as a star is affected in opposite ways by her social network cohesion with star versus non-star collaborators:*

> ***H2a.*** *Increasing network cohesion with* star *collaborators has a* positive *effect on the focal designer's likelihood of becoming a star.*
>
> ***H2b.*** *Increasing network cohesion with* non-star *collaborators has a* negative *effect on the focal designer's likelihood of becoming a star.*

Expertise similarity

As designers 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 areas of design expertise. We therefore define *expertise similarity* as the extent to which the focal designer's expertise is in areas similar to her collaborator's areas of expertise.

As was the case for network cohesion, expertise similarity has two opposing effects on the focal designer's chances of becoming a creative star. On the one hand, similarity with regard to expertise reflects common professional experiences; thus the designers have been working in the same "idea space" (Azoulay et al. 2010). The consequences of this similarity include sharing a knowledge base, which increases the frequency of communication (Reagans et al. 2005). In addition, findings from the literature on absorptive capacity indicate that one can more easily acquire new knowledge that is more closely related to the knowledge one already has (Cohen and Levinthal 1990, Shaker A. Zahra and George 2002); collaborators find it relatively more difficult to transmit and acquire new ideas across distinct areas of expertise (Reagans and McEvily 2003). A common basis of similar experiences thus simplifies and furthers the exchange of ideas between individuals in the same field. It follows that increased expertise similarity facilitates the transfer of knowledge (Reagans and McEvily 2003)—a dynamic that is accentuated when the exchanged knowledge is tacit and/or complex (Hansen 1999, Zander and Kogut 1995).

On the other hand, there are potential downsides to high levels of expertise similarity. Similar experiences and backgrounds in areas that are common to both the focal designer and her collaborators can inhibit the combining of hitherto unconnected knowledge domains. Excessive common knowledge is thus likely to result in knowledge redundancy, which in turn could limit the generation of creative ideas (Rodan and Galunic 2004, Sosa 2011).

Just as with network cohesion, the relevance of these arguments depends on distinguishing collaborators based on their quality. A star collaboration should benefit from expertise similarity. The star has already developed extensive (tacit) knowledge of the field. Even if a collaborating focal designer has worked in the same domain as the star, the two designers need not (and almost certainly do not) possess the same level of subject mastery. Star designers have considerably more in-depth (tacit) knowledge than do non-stars. A focal (non-star) designer with at least a basic understanding of design domain knowledge shared with her star collaborator can be expected to ask insightful questions, to comprehend the advice given by the star, and to assimilate that advice for future use. Thus working with a star designer who shares similar areas of expertise considerably increases the focal designer's exposure to otherwise inaccessible tacit design knowledge. Fewer new combinations of ideas may arise in such collaborations, but that downside of expertise similarity is more than compensated for by its benefit of facilitating knowledge transfer—especially the transfer of tacit knowledge.

For a non-star collaboration, the balance again reverses. If there is high expertise similarity between the focal designer and her non-star collaborators, then the focal designer is relatively less exposed to a diversity of perspectives and breadth of knowledge (Fleming, Mingo, et al. 2007, Milliken et al. 2003)—the raw material for the creation of novel ideas. Recall that there is not much difference in knowledge between the focal designer and non-star collaborators; therefore, despite expertise similarity continuing to facilitate the exchange of knowledge, there is little that the focal designer can learn in such collaborations. Yet if even a non-star collaborator possesses expertise in different knowledge domains (so that expertise similarity is low), then the mere existence of that diverse perspective can inspire creativity (Hargadon and Sutton 1997, Rodan and Galunic 2004, Sosa 2011) and, perhaps, lead to breakthrough ideas (Singh and Fleming 2010). So in these collaborations, a high level of expertise similarity will hinder the cross-pollination of ideas without facilitating design knowledge transfer.

After considering these various effects of expertise similarity, we are led to propose the following two-part hypothesis.

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

> ***H3a.*** *Increasing expertise similarity with* star *collaborators has a* positive *effect on the focal designer's likelihood of becoming a star.*

H3b. *Increasing expertise similarity with* non-star *collaborators has a* negative *effect on the focal designer's likelihood of becoming a star.*

3. DATA, METHODS, AND ANALYSES

To test our hypotheses, we need a longitudinal data set 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 of documentation on creative output (Chan et al. 2015). We obtained our design patent data by "crawling" the website of the US Patent and Trademark Office.

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 (appearance) of an item whereas a utility patent protects an item's functionality. Because design patents focus on innovation in form, not function, the scope of such patents is limited to the "overall ornamental visual impression" (USPTO 2015).

Although our study is the first to use design patent data on a large scale in an organizational context, we can draw on and extend methods developed in the context of utility patents. Many methodological concepts carry over because, under the US patenting system, design and utility patents share many common characteristics. First, the data's longitudinal nature provides rich historical information at both the personal and network levels. We can track such information through first and subsequent patent applications, which document how a designer's collaborative patterns evolve over time. Hence we can construct a comprehensive collaborative history for all individual designers in our database.[2] Second, there is a tradition of using patent data to analyze creativity because such data enable one to quantify creative output (Shalley & Zhou, 2008) and so ease the long-standing difficulty of measuring innovation. Creativity is normally understood to involve both novelty and usefulness, and the reliability and objectivity of the patent approval process ensures a minimum level of novelty. Third, using patent *citations* as a proxy for the influence of an invention—and hence of its inventors—is a practice widely employed by researchers to capture, to some degree, the usefulness of patents (Jaffe, Trajtenberg & Romer, 2002): the more citations a patent receives, the more it is viewed as an inspiration for subsequent creative endeavors (Audia & Goncalo, 2007). The citations that a patent receives have thus been accepted in the literature as reliable and systematic indicators of an invention's economic, social, and technological success (Jaffe et al. 2002, Singh and Fleming 2010). This approach is especially vital for analyzing creative performance in the context of design, since what constitutes a "good design" is more elusive than identifying the characteristics of a great scientific discovery.

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 as regards to both the cutoff point and the preceding time window. 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 (Singh and Fleming 2010) use a 5% cutoff—for both the upper and lower tails of the distribution—when identifying (respectively) breakthrough and poor inventions. As for the time window, scholars who study archival data have used windows ranging from three years (Fleming, Mingo & Chen,

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

2007) to five years (McFayden and Cannella 2004) when assessing an inventor's performance. Time windows are used in such research because a patent's citations vary over time as a function of its relevance, economic value, and product category. The number of citations typically decreases with the passage of time (Trajtenberg 1990), so the most reasonable approach is to count only those citations received within the recent past. We tested our hypotheses by setting the cutoffs at 1%, 2%, and 5% with three year rolling window, and by testing 2% cutoff using rolling time windows of three, five, and seven years (as well as no rolling window at all). 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% threshold. Although we processed all the design patents granted in the US during the 1975-2010 period, our observation window ranges from year 1985 to year 2004 because we needed to allow for some time before and after such observation window for designers to accumulate enough citations to establish a relatively stable popularity index. In our observation window, there were 144,288 designers who had been 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). In line with prior research examining stars (Grigoriou and Rothaermel 2014, Groysberg et al. 2011) , we assume that a star designer will remain a star during the study's observation window.

3.3. Collaborating with a star designer

In this section we carry out two steps before formally testing our hypotheses in Section 3.4. First, we discuss a coarsened exact matching (CEM) sample procedure, which allows us to mitigate any selection bias concerns when we later examine the effects of collaboration with a star designer. Second, we

[3] It is reassuring to know that our method correctly identified well known star designers such as Jony Ive, Robert Brunner, Steve Jobs, Frank Nuovo, Phillippe Starck, and Yves Behar (to name just a few) as star designers.
[4] This proportion is not at odds with our definition of a star (i.e., an inventor in the top 2% of designers based on their popularity index on a given date): 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.

complete a difference-in-differences analysis to provide empirical evidence of the focal designer's benefits from collaborating with a star.

3.3.1. Constructing the matched samples

Our baseline hypothesis (H1) argues that a focal designer's chances of emerging as a star are substantially more affected by collaborating with a star designer than with a non-star designer. Perhaps the foremost challenge in testing such a hypothesis is that the inherent capabilities (quality) of the focal designer could drive not only the focal designer's chance of working with a star but also the likelihood of that designer emerging as star herself. We address this endogeneity concern by employing a CEM procedure to identify a sample in which selection issues are significantly mitigated (Aggarwal and Hsu 2014, Azoulay et al. 2010, Iacus et al. 2011, 2012, Oettl 2012, Singh and Agrawal 2010). The CEM procedure helps to balance the (pre-treatment) focal and control subsamples, which it does by constructing matched pairs that are strongly similar 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 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 variables that could correlate with engaging in a star collaboration and also with the focal designer herself becoming a star. Hence it is necessary to investigate the quality factors of focal designers. We argue that a star's choice of collaborator is likely influenced by the focal designer's own patenting success, the tendency of that designer to collaborate, and the amount of attention garnered in the patent community by the focal designer's previous patents. We follow Bode et al. (2015) and perform a logit regression to test whether such quality factors of a designer could indeed be associated with the probability of entering into collaboration with a star designer. Table 1 shows the results, where the dependent variable is "entering into collaboration with a star designer". The reported coefficient estimates indicate that the following six characteristics are indeed significant determinants of a focal designer's collaborating with a star designer: (i) year of the focal designer's first patent application; (ii) 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, which is a categorical variable that captures 33 major design classes (USPTO 2015). Column 1 in Table 1 excludes and Column 2 includes the major class dummies, most of which exhibit significant coefficients. Hence we use all the six variables as pre-treatment observables to build our CEM sample.

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

Variable	[1]	[2]
Year of first patent application	-0.014**	-0.01
	(0.007)	(0.007)
Career age	0.112***	0.115***
	(0.006)	(0.006)
Number of non-guru collaborators	-0.130***	-0.145***
	(0.015)	(0.016)
Number of patents	0.053***	0.049***
	(0.004)	(0.004)
Number of citers	0.001***	0.001***
	(0.000)	(0.000)
Major patent class dummies	no	yes
Wald CHI sq	1366	1572
Log likelihood	-5285	-5169

*Notes. Observations = 147081. * p<0.10, ** p<0.05, *** p<0.01*

Building the CEM sample, we examine our entire sample of designers to identify pairs of designers who were similar, based on the six key pre-treatment observables, at the time of the treatment event (star collaboration). We ensure that each pair's members begin patenting in the same year (*Year of first patent application*) and that their *Career age* is the same at the treatment event; that is, we use one "bucket" for each those two variables to ensure that each pair's members satisfied both criteria. Furthermore, we ensure that matched pair members have designed products in the same USPTO patent classes (*Major patent class*), exhibit a similar pattern of collaboration (*Number of non-star collaborators*), have displayed comparable levels of design productivity (*Number of patents*), and are the object of similar attention from other designers (*Number of citers*). We match the two groups—that is, those who do or do not undergo the treatment event—using four discrete buckets for each of these last four variables.

In order to identify those effects of a star collaboration that are in excess of the effects of a non-star collaboration, we ensure that each focal designer has engaged in at least one (non-star) collaboration prior to the treatment event.[5] As in the extant literature, we match each focal 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 focal designers who end up collaborating with star designers and the control group: their respective covariates are well balanced, and their mean values are not statistically different (at the 5% level). This outcome illustrates the advantage of CEM over the widely used "propensity score matching" approach, which does not guarantee a balance between the two matched groups (Iacus et al. 2012).

Table 2. Summary Statistics for Matched Samples

	Focal 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

Notes. Designers = 14250. Major patent class is a categorical variable and it is the same for a matched pair of focal and control designer by construction (not shown in the table).

A first examination of the CEM sample (see Table 3), which consists of strongly similar matched pairs of designers, yields *preliminary* evidence that—in line with H1—a higher percentage of the focal group's designers emerge as stars. More specifically: 16% of the *focal* designers who collaborated with stars

[5] The results are similar when instead we use a more general sample that includes "lone" designers whose first collaborator was a star. Both samples are used in Section 3.4.1, where we formally test our baseline hypothesis H1.

emerged later on as stars in their own right, whereas the corresponding figure for the CEM sample's *control* designers is only 9%. In Section 3.4.1 we shall conduct a more rigorous estimation using event history analysis, which confirms that the treatment effect is a highly significant one.

Table 3. Ratio of Star's Emergence among Treatment vs. Control Designers

	# of designers	*# of designer's emergence*	*Ratio*
Focal designers	7125	1107	0.16
Control designers	7125	662	0.09
Overall	14250	1769	

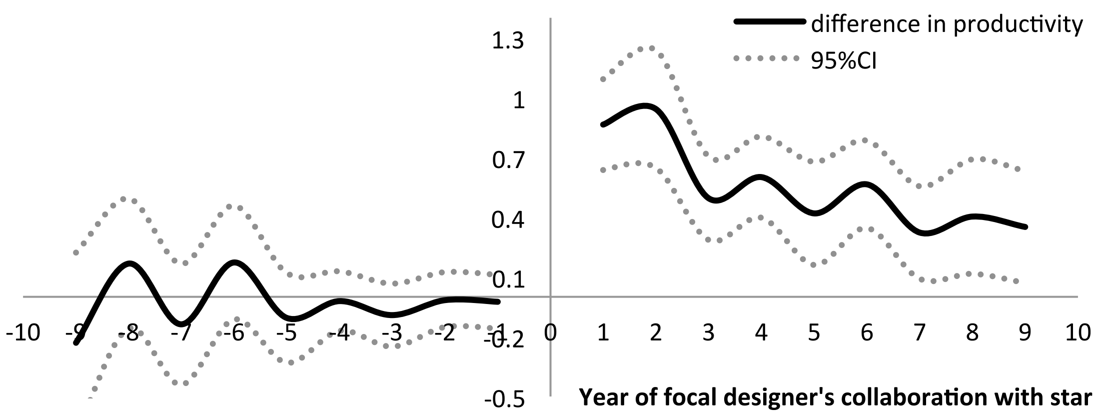
Before testing our baseline hypothesis formally, we examine the CEM sample more closely to assess whether collaborating with a star translates into increased design productivity of the focal designer. Testing for such a benefit proceeds via a difference-in-differences (DID) analysis based on our CEM sample.

3.3.2. Effects of star collaboration: A difference-in-differences analysis

We start by examining the benefits of a star collaboration that are likely to be due to effective transfer of design knowledge; for this purpose we use the number of patents applied for by the designer in each year as a proxy for her productivity and ability to create novel designs. In particular, we examine the difference in the number of patents applied for by the focal and the control designers both before and after the treatment event. This procedure requires additional criteria to be applied to our CEM sample. First, we must observe all of the focal and control designers for the same extended time period; following Singh and Agrawal (2010), we use a 12-year observation window. Second, deriving meaningful comparisons between pre- and post-treatment performance requires that our focal designers engage in their first star collaboration some time between the 3rd and the 10th years (inclusive) *following* the year of their first patent application. Thus both the pre- and post-treatment periods for all designers of interest are at least two years long. Our DID sample consists of 722 individuals, 361 each in the treatment and control groups.

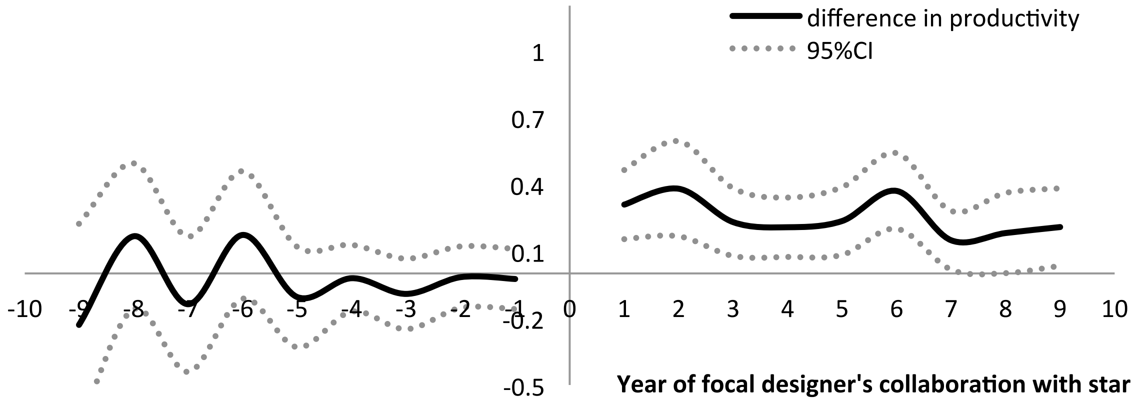
As shown by the graph plotted in Figure 1, the productivity difference between these two groups is statistically indistinguishable before the treatment event. However, there is a positive and significant boost (at the 95% confidence interval) in productivity among the focal designers after collaborating with stars. Furthermore, this difference in productivity persists long after treatment occurred.

Figure 1. Difference in the Number of Patents between Focal and Control Groups (All Patents)



One might reasonably object that the number of patents for which our focal designers apply includes patents filed in collaboration with the star designers, who tend to be highly productive; as a result, we may have overestimated the focal group's true productivity. To address that concern, we perform an additional analysis in which productivity is measured while *excluding* those patents filed in conjunction with a star designer—that is, we count only single-author patents and patents authored with non-star collaborators. Figure 2 reveals that, even after excluding patents filed with a star collaborator, there is a significant and consistent (albeit somewhat smaller) increase in the productivity of focal designers. Finally, an even more stringent test (results not reported here) that excludes all but single-authored patents likewise finds that productivity increases after a star collaboration. This analysis empirically supports the notion that collaborating with a star designer influences significantly the capability of the focal designer to produce more novel ideas. Next, we need to rigorously test if such benefits translate into higher chances of the focal designer becoming a star designer herself.

Figure 2. Difference in the Number of Patents between Focal and Control Groups (Patents without Star Collaborators)



3.4. Hypotheses testing with event history analysis

In this section we test H1 directly by way of an event history analysis, which 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). The data that we use 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 at a later date.

As is customary in event history analysis, we employ maximum likelihood techniques to estimate Cox proportional hazard models on survival-time data (Cox 1972). The “hazard” here is the likelihood of a designer becoming a star during the time window of observation (1985-2004). In our study, observations include designers who have been awarded a design patent and so are “at risk” of becoming a star. For estimation purposes, we use the *stcox* command in Stata 14.0.

3.4.1. Testing Hypothesis 1 against the CEM sample

As a first formal analysis, we test the baseline hypothesis using three samples (with equal numbers of focal and control designers) based on our CEM analysis. These samples reflect more to less stringent criteria regarding collaboration patterns before the first star collaboration (i.e., prior to the treatment event): (1) the focal designer has had at least one non-star collaborator before the treatment event (this is the CEM sample, which contains 14,250 designers, that we have used so far); (2) the focal designer has had no collaboration at all, so the treatment event is the first collaboration (this sample contains 4,486 designers); and (3) a sample comprising both of the previous two (this sample therefore contains 18,736 designers). Formally, we create an indicator variable: for the focal designers (who collaborate with a star designer) the indicator takes the value 1 and for the control designers (who do not collaborate with a star designer) it takes the value 0. We control also for other possible sources of heterogeneity in the creative abilities of all the sample's designers—that is, sources for which the CEM approach does not explicitly control—by constructing the six additional variables described next.

Assignee's past patents. The assignee is usually the organization with which the designer is associated and also the organization owning the patent. According to Audia and Goncalo (2007), the total number of patents held by an organization is a good proxy for the scale of its innovation activities. Trajtenberg (1990) shows that a simple patent count is strongly correlated with the patenting firm's innovativeness. The most innovative organizations are likely to present excellent career opportunities and hence can afford to be selective in their hiring; they tend to attract and retain the field's best applicants. Thus an organization's innovativeness, as measured by its patent stock, is associated with the quality of its staff. We use patent records to identify each designer's assignee organization and also to calculate that organization's cumulative number of patents until time t.

Mobility. The number of organizations with which an individual has been associated is strongly correlated with that individual's experience (Fujiwara-Greve and Greve 2000, Mincer and Jovanovic 1981). So in our study, much as in Fleming, King, and Juda (2007), the *Mobility* variable counts the number of unique assignees associated with the focal designer—as evidenced by the designer's patents awarded until time t.

Class diversity. Audia and Goncalo (2007) report that, in the hard disk drive industry, more highly skilled patenting inventors are more likely to venture into different innovation areas as they accumulate experience. It is therefore plausible that the diversity of classes within which a designer has secured patents can serve as a proxy for her capability to think and act in a divergent way (an important capability in design). Hence our *Class diversity* variable is a count of the number of unique subclasses in which the focal designer has been awarded a patent up to time t.

Location diversity. There is abundant evidence that experiences living abroad, or even the mere exposure to different cultures, increases individual creativity (Leung, Maddux, Galinsky & Chiu, 2008). That enhancement may result from adapting to different cultures, gaining access to novel ideas, or experiencing "conceptual expansion" (Maddux & Galinsky, 2009). All these factors diversify an individual's outlook and so make the focal designer a more capable and valuable collaborator. 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), it is important to control for any such trends in the number of patents granted in each of the major patent class. Hence, we count, *for each year*, the total number of patents granted (to all designers) 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. For each designer, it indicates whether the designer first patented in one of the five-year intervals during the 1985–2004 period. We remark that our results are robust to the exclusion of these cohort dummies.

We use the three CEM samples described previously to estimate a Cox proportional hazard model on the likelihood of star emergence. Table 4 presents the descriptive statistics for and correlations between our variables. As can be seen in Table 5, the dummy variables in all models (columns [1]–[6]) are positive and strongly significant ($p < .01$), supporting H1. Models [1] and [2], which use the sample in which the focal designer collaborates at least once with a non-star before the treatment event, show that the indicator has a positive and highly significant coefficient in a model without general controls (0.283, $p < .01$) and also in a model with some general controls (0.219, $p < .01$). It follows from model 2 that our focal designers are 24% ($e^{0.219} - 1 = 0.24$) more likely to emerge as a star than our control designers. Models [3] and [4] report like evidence for the case when the focal designer was a lone designer before her first collaboration with a star designer, which confirms the notion that a star collaboration is more beneficial to star emergence than not collaborating at all. Our hypothesis H1 is also supported when we use the most general CEM sample which includes all the focal designers; see Models [5] and [6].

Table 4. Descriptive Statistics and Correlation of Variables

	Variable	Mean	S.D.	1	2	3	4	5
1	*Focal designer dummy*	0.56	0.50					
2	*Assignee's past patents(Ln)*	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 (Ln)*	6.72	0.68	0.03	0.03	0.13	0.07	0.03

Table 5. Effect of Star Collaboration on Focal Designer's Emergence as Star (Proportional Hazard Models)

Variable	[1]	[2]	[3]	[4]	[5]	[6]
Focal designer dummy	0.283***	0.219***	0.670***	0.621***	0.378***	0.274***
	(0.025)	(0.025)	(0.047)	(0.048)	(0.022)	(0.028)
Assignee's past patents		0.003		0.013		0.003
		(0.006)		(0.01)		(0.005)
Class diversity		0.306***		0.343***		0.276***
		(0.028)		(0.043)		(0.012)
Mobility		0.231***		0.307***		0.058*
		(0.034)		(0.076)		(0.032)
Location diversity		0.751***		0.664***		0.408***
		(0.121)		(0.157)		(0.115)
Patent stock year		0.652***		0.539***		0.528***
		(0.058)		(0.08)		(0.049)
Cohort	no	yes	no	yes	no	yes
No of designers	14250	14250	4486	4486	18736	18736
Log likelihood	-15689	-15210	-4931	-4795	-22048	-21444

Notes. * p<0.10, ** p<0.05, *** p<0.01; Column (1) and (2) use the CEM sample that the focal designer has had a non-star collaboration before the treatment event; Column (2) and (3) use the CEM sample that the focal designer has had no collaboration before the treatment event; Column (5) and (6) use previous two sample combined.

3.4.2. Testing the effects of network cohesion and expertise similarity

We have provided evidence that star collaborations differ from non-star collaborations in that the former increase a focal designer's likelihood of becoming a star. In this section we test Hypotheses H2 and H3 and show how collaborating with a star differs from collaborating with a non-star as evidenced by the effects of network cohesion and expertise similarity. Because we posit moderating effects of star versus non-star collaborations on a third variable (i.e., network cohesion or expertise similarity), we must use a sample that differs from the one used to test H1; in particular, we must focus on designers who have a non-star *and* a star collaborator in their network. This criterion selects 27,278 designer–patent observations in our study's 1985–2004 window.

Independent variables

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 via $t \in [1, T]$; here t is an integer and T is the last instance of a patent application in our data. In what follows, we use $\boldsymbol{H}_{it}$ and $\boldsymbol{L}_{it}$ to denote (respectively) the sets of stars and non-stars with which focal designer i has worked until time t. Let $\boldsymbol{F}_{it}$ be the set of past collaborators of the focal designer i up to time t; analogously, let $\boldsymbol{G}_{jt}$ be the set of past collaborators of star j at time t.

Direct ties to collaborators. In order to re-test our baseline hypothesis (H1), we measure the focal designer's direct ties to stars and to non-stars. Thus *Direct ties to stars* is a count of the number of a focal designer i's unique star collaborators until time t (i.e., $|\boldsymbol{H}_{it}|$). The more direct ties between a designer and stars, the more experience and benefits that the focal designer has accumulated by working with those stars. Analogously, *Direct ties to non-stars* counts the number of a focal designer i's unique non-star collaborators until time t (i.e., $|\boldsymbol{L}_{it}|$); this variable is a proxy for the focal designer's past experience working with non-stars.

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. In order to measure network cohesion, we start with the focal designer's local network *density*, which is widely accepted as a reliable indicator of social network cohesion (Fleming, Mingo, et al. 2007, Gargiulo et al. 2009, Obstfeld 2005, Podolny and Baron 1997). A focal actor's ego network density is defined as the ratio of existing ties in the focal actor's network out of all possible ties, or equivalently, it is the number of closed triads divided by the number of possible triads with the focal actor. Importantly, local density thus captures the average fraction of common third parties within the focal actor's network. For our study, network cohesion must be defined with respect to two types of collaborators: stars and non-stars. Following the definition of the focal actor's network density, 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 star designers ($j \in \boldsymbol{H}_{it}$). Formally, we have

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

which expresses the average fraction—in the focal designer's network—of common third parties with a star designer. At the extremes, this continuous measure is equal to 0 if there are *no* third parties in common with any star designer 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 measure *Network cohesion with non-stars* similarly as the average fraction—in the focal designer's network—of common third parties with non-star designers.

Expertise similarity. Hypothesis H3 cannot be tested unless we are able to identify, for any moment in time, the areas of expertise of the designers in our database. For this purpose we rely on the classification of design patents made by the USPTO, which sorts design patents in terms of their intended use so that "industrial designs that have the same function are generally collected in the same Design class" (USPTO 2015). Each major class is itself divided into subclasses that pertain to a more "specific type of industrial design". Designs in the respective subclasses require substantially different skill sets to produce, so each subclass can be considered a distinct area of expertise.

Following previous work that measures knowledge overlaps between actors (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 i and a star collaborator j divided by the focal designer's areas of expertise. Specifically, let $\boldsymbol{K_{it}}$ be the set of subclasses in which the focal designer $\boldsymbol{i}$ has patented until time t, and let $\boldsymbol{K_{jt}}$ be the set of subclasses in which star j ($j \in \boldsymbol{H_{it}}$) has patented until time $\boldsymbol{t}$. We define expertise similarity with stars from the focal designer's perspective as: $ES_{it} = \frac{\sum_{j \in \boldsymbol{H_{it}}}(|\boldsymbol{K_{it}} \cap \boldsymbol{K_{jt}}|/|\boldsymbol{K_{it}}|)}{|\boldsymbol{H_{it}}|}$. This variable, too, ranges from 0 to 1: here 0 indicates no expertise similarity between the focal designer and all her star collaborators whereas 1 indicates a perfect overlap between the parties' areas of expertise. We analogously define *Expertise similarity with non-stars* as the average fraction of areas of expertise that are common to both the focal designer i and a non-star collaborator j divided by the number of the focal designer's areas of expertise.

Additional control variables

In order to identify the different effects that star and non-star collaborators have on network cohesion and expertise similarity, we must control for characteristics not only of the focal designer but also of her star and non-star collaborators. Hence, in addition to the general control variables defined above, we include as controls the following three variables; each is defined for both star and non-star collaborators.

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. With respect to i, we define $Star's\ direct\ ties_{it} = \left|\bigcup_{j \in \boldsymbol{H_{it}}} \boldsymbol{G}_{jt}\right|$. Since collaboration consumes both time and energy, it follows that 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 and strength of collaboration, we adopt a strength-of-tie measure based on observations of repeated collaborations (Fleming, Mingo & Chen, 2007; Hansen, 1999; McFadyen & Cannella, 2004). In other words, our variable is a proxy for the focal designer's tendency to collaborate repeatedly with the same star(s). Formally, we put $c_{ijt_0} = 1$ if designers i and j collaborate at time t_0; then we define

$$Repeated\ collaborations\ with\ stars_{it} = \frac{\sum_{t_0=1}^{t-1} \sum_{j \in \boldsymbol{H}_{it}} c_{ijt_0}}{|\boldsymbol{H}_{it}|}$$

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. In the same way we measure *Repeated collaborations with non-stars.*

Star's attention pool. As a control for the social attention that collaborating with a star may bring to the focal designer's work, we count the number of designers citing the star's patents in their own patent applications. We may suppose that a star whose patents are cited by more designers has accumulated more attention; that is, a more highly cited star has a larger group or pool of followers. A star with a larger following can bestow more social attention on collaborators than can a star with a smaller following. We therefore define the *Star's attention pool* as the number of individuals who have, up to time t, cited the star's patents. Let p_f be a patent in the set $\boldsymbol{P_f}$ of patents granted to a focal star f. Then c_f is a *citing* patent if p_f is in the citation list of c_f. We use $\boldsymbol{C_f}$ to denote the set of citing patents such that any $c_f \in \boldsymbol{C_f}$ cites some $p_f \in \boldsymbol{P_f}$. Let $\boldsymbol{A_{fc}}$ signify set of patent c_f's co-authors. As usual, the subscript t stands for "up to time t". We can now formally define the attention pool of a star f until time t as $Star's\ attention\ pool_{ft} = \sum_{c_f \in \boldsymbol{C_{ft}}} |\boldsymbol{A_{fc}}|$; the *Non-star's attention pool* is defined analogously.

Table 6 provides summary statistics and correlations for all our defined variables. Table 7 reports the results of the event history analysis we used to test H2 and H3.

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

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

Model 1 in Table 6 includes all the control variables. Model 2 is a partial model that incorporates the focal designer's number of star and non-star collaborators. Model 3 includes the network cohesion variables used to test H2, and Model 4 includes the expertise similarity variables used to test H3. Model 5 is the full model, which, in the following, is used to test all our hypotheses and then to interpret the results.

Table 7. Proportional Hazard Model of Designer Emergence As Star

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

Notes: n=27,278. Robust standard errors are reported in parentheses. All models control for cohort dummy variables.
* p<0.10, ** p<0.05, *** p<0.01

Before testing H2 and H3, as a side aspect we retest H1 in the sample used for testing H2 and H3. Clearly, the coefficients for *Direct ties to stars* (0.673, $p < .01$) and also for *Direct ties to non-stars* (0.426, $p < .01$) are both positive and significant. These coefficients imply that any collaboration is preferable to no collaboration (the omitted case). We can further interpret the relative effect of collaborating with stars versus non-stars via inspection of their respective hazard ratios. A one-unit increase in (the natural logarithm, (Ln+1), of *Direct ties to stars* makes the focal designer 1.96 times ($e^{0.673} = 1.96$) more likely to emerge as a star (as compared with a designer who has no ties). Similarly, a one-unit increase in *Direct ties to non-stars* (Ln+1) yields a corresponding factor of $e^{0.426} = 1.53$. Collaborating with stars rather than non-stars increases the hazard rate by a factor of 1.28 (=1.96/1.53), and the difference between these two collaboration effects is statistically significant ($p < .017$). Thus the data support our baseline hypothesis H1 that a star collaboration is significantly more beneficial than a non-star collaboration—even for the sample of designers who have collaborated at least once with both a star and a non-star.

The results reported in Table 7 also support our network cohesion hypothesis (H2), which posits that increased network cohesion has a positive (resp. negative) effect on the outcomes of collaborations with star (resp. non-star) designers. Model 5 strongly supports both H2a and H2b. The positive and significant coefficient for *Network cohesion with stars* (0.371; $p < .05$) indicates that, for designers who collaborate with both stars and non-stars, having a more cohesive social network with a star collaborator increases, on average, the focal designer's likelihood of becoming a star—in line with H2a. 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 probability that the focal designer will become a star. In contrast, 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 H2b. 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 ($e^{(-1.650\times0.24)} - 1 = -0.33$).

Hypothesis H3 posits that greater expertise similarity with a star (resp. non-star) collaborator increases (resp. decreases) the focal designer's odds of emerging as a star. Our results strongly support H3. 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 H3a. An increase of one standard deviation in *Expertise similarity with stars* increases the probability of becoming a star by 15% ($e^{(0.469\times0.29)} - 1 = 0.15$). In contrast, the negative and significant coefficient for *Expertise similarity with non-stars* (−1.032, $p < .01$) indicates that designers having greater expertise similarity with such non-star collaborators thereby reduce significantly their probability of becoming a star. Here an increase of one standard deviation in *Expertise similarity with non-stars reduces* the likelihood of emergence as a star by 27% ($e^{(-1.032\times0.31)} - 1 = -0.27$).

4. ROBUSTNESS CHECKS

We explore the range of conditions under which our claims hold by conducting extensive robustness analyses. In particular, we check the robustness of alternative cutoff points for identifying star designers. In our analysis, a star is defined as any designer whose popularity index—as measured by citations in a three-year rolling window—is in the top 2% of all designers in our database. The robustness tests systematically vary the two parameters in this definition to match alternative values proposed in the literature (e.g., Ahuja & Lampert, 2001; McFadyen & Cannella, 2004; Singh & Fleming, 2010). First, we hold constant our main model's 2% cutoff while evaluating the effect of replacing that model's three-year time window with a five-year and a seven-year window and also with a non-rolling time window (i.e., one that extends back to the start of our observation period). Second, we hold the three-year rolling window constant and compare results under various cutoff values (1%, and 5%) for the popularity index. The tests, whose results are reported in Table 8, show that our hypotheses are overwhelmingly robust to these variations in the definition of a star. The difference between direct ties to stars and direct ties to non-stars is positive and significant across all the models; in addition, the effect on emergence of network cohesion with stars (H2a) is positive and significant in all models (except for Model 6, in which the effect is positive but not significant) and, as expected, the effect of such cohesion with non-stars (H2b) is negative and significant across all models. Finally, the effect on emergence of expertise similarity with stars is positive and significant (H3a) and with non-stars is negative and significant (H3b) across all the models.[6]

Table 8. Robustness Checks Using Various Definitions of "Star"

Variable	Star definition:	[1] 2%3yr	[2] 2%5yr	[3] 2%7yr	[4] 2%allyr	[5] 1%3yr	[6] 5%3yr
Direct ties to stars (H1)		0.673***	0.723***	0.711***	0.686***	0.837***	0.931***
		(0.089)	(0.105)	(0.111)	(0.132)	(0.113)	(0.066)
Direct ties to non-stars (H1)		0.426***	0.354***	0.416***	0.545***	0.479***	0.056
		(0.051)	(0.057)	(0.062)	(0.074)	(0.083)	(0.042)
Social cohesion with stars (H2a)		0.371**	0.475**	0.508**	0.638***	0.622***	-0.212
		(0.168)	(0.191)	(0.201)	(0.227)	(0.218)	(0.156)
Social cohesion with non-stars (H2b)		-1.650***	-1.714***	-1.798***	-2.177***	-1.394***	-0.925***
		(0.205)	(0.235)	(0.246)	(0.276)	(0.25)	(0.174)
Expertise similarity with stars (H3a)		0.469***	0.435***	0.553***	0.681***	0.876***	0.271**
		(0.131)	(0.142)	(0.152)	(0.173)	(0.175)	(0.124)
Expertise sim. with non-stars (H3b)		-1.032***	-1.196***	-1.132***	-1.148***	-1.524***	-0.728***
		(0.161)	(0.181)	(0.188)	(0.227)	(0.22)	(0.141)
Controls							
Stars' direct ties		-0.333***	-0.352***	-0.379***	-0.389***	-0.486***	-0.273***
		(0.045)	(0.053)	(0.055)	(0.064)	(0.061)	(0.039)
Non-stars' direct ties		-0.377***	-0.352***	-0.356***	-0.385***	-0.168**	-0.184***
		(0.044)	(0.05)	(0.054)	(0.063)	(0.07)	(0.04)
Attention pool of stars		0.153***	0.220***	0.251***	0.272***	0.297***	0.239***
		(0.038)	(0.045)	(0.048)	(0.059)	(0.059)	(0.035)
Attention pool non-stars		0.311***	0.328***	0.332***	0.351***	0.239***	0.229***
		(0.017)	(0.019)	(0.02)	(0.023)	(0.031)	(0.018)
Repeated collaboration with stars		-0.025	-0.013	-0.014	-0.013	-0.01	0.058***
		(0.016)	(0.013)	(0.013)	(0.011)	(0.011)	(0.013)
Repeated collaboration with non-stars		0.114***	0.098***	0.102***	0.111***	0.097***	0.004
		(0.018)	(0.015)	(0.014)	(0.013)	(0.014)	(0.016)
Assignee's past patents		0.116***	-0.003	-0.009	0.002	0.150***	-0.002
		(0.013)	(0.006)	(0.006)	(0.007)	(0.018)	(0.004)
Class diversity		0.127***	0.127***	0.124***	0.107***	0.116***	0.115***
		(0.011)	(0.012)	(0.011)	(0.01)	(0.011)	(0.016)
Mobility		0.028	-0.040*	-0.040*	-0.032	0.047*	0.019
		(0.024)	(0.022)	(0.021)	(0.022)	(0.025)	(0.023)
Location diversity		0.007	0.099	-0.003	0.07	0.009	0.068
		(0.087)	(0.082)	(0.081)	(0.083)	(0.089)	(0.084)
Patent stock year		0.145***	0.127***	0.098**	-0.031	0.180***	0.151***
		(0.037)	(0.04)	(0.043)	(0.048)	(0.049)	(0.031)
Cohort		Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood		-20509	-16352	-14076	-9691	-10471	-23861
Observations		27278	26027	25087	23323	22263	15546

* p<0.10, ** p<0.05, *** p<0.01

[6] It is not surprising to see that as the cut-off threshold increases (e.g., 5% in Model 6 of Table 8) the effects of both network cohesion and expertise similarity with stars becomes less positive. For as we increase the cut-off threshold the star and the non-star converge and the distinction between stars and non-stars becomes less significant.

5. DISCUSSION AND CONCLUSION

The discipline of design is receiving increased attention from the business community. In many industries, the core functionality of competing products has been converging and so functionality has lost some of its power to create product differentiation. The design (or the "form") of products, rather than their functionality, has therefore been gaining importance (Ulrich 2011b)—a trend confirmed by many in the business press and in practitioner circles (BBC 2013, Brown 2008, Brunner et al. 2008, Miller 2013). The field of product design is one in which the star's role figures prominently. In categories as varied as clothing, cars, furniture, computers, and communications equipment, star designers have become household names; in fact, they exert considerable influence over how entire industries conceive their next-generation products (Ulrich 2011a, Utterback et al. 2006). As a result, each firm competes with its rivals to recruit top designers so that it can build design capabilities and nurture its own design talents.

This paper sheds light on two areas that have received little attention in the literature despite being crucial for innovation management. First, we investigate the antecedents of star emergence and in particular the role played, in star emergence, by interpersonal collaboration with stars. Second, because collaborating with stars differs substantially from collaborating with non-stars, we address the question of how collaborator quality (star versus non-star) moderates the effect of social- and knowledge-related factors on the focal designer's emergence as a star. Overall, our findings—which highlight the distinct roles played by stars and non-stars in collaborative settings—uncover an important yet heretofore unexplored dimension that is highly relevant to the literature on interpersonal collaboration networks in creative contexts (Reagans and McEvily 2003, Sosa 2011, Tortoriello and Krackhardt 2010): the quality of a collaborator.

Both of our contributions relate to a growing stream of studies in creativity research that aim to identify the drivers of outstanding versus average performance (Ahuja and Lampert 2001, Girotra et al. 2010, Singh and Fleming 2010, Terwiesch and Ulrich 2009). Previous work in this area adopts the *idea* as the unit of analysis and explores the emergence of breakthrough ideas, but our study focuses on the *individual*.

Our empirical baseline result distinguishes among collaborators based on their standing in the design community. We establish that star collaborators are considerably *more* instrumental than non-star collaborators in a focal designer's transition to star status. We argue that collaboration with a star is more fruitful because the significant tacit (design) knowledge differential between star and non-star designers leads to superior (design) knowledge transfer. This dynamic helps us identify an important antecedent to outstanding performance at the individual level, which have been neglected by the prior literature focusing on stars (Azoulay et al. 2010, Groysberg et al. 2011).

It may seem intuitive that collaborating with stars rather than non-stars raises considerably the focal designer's likelihood of achieving stardom. Yet confirming this notion empirically, as we do in this paper, serves to answer the counterargument that star collaboration could be less beneficial given the constraints on a star's time and dedication; empirical confirmation also offers a unique opportunity to deepen our understanding of the determinants of knowledge transfer within interpersonal collaboration networks. Because a focal designer can collaborate with actors of distinguishable quality (i.e., stars vs. non-stars), we are able to evaluate how collaborator quality moderates the effect of two key determinants of effective knowledge transfer—namely, network cohesion and expertise similarity—on the likelihood that a focal designer achieves outstanding creative performance.

Our results reveal that, contingent on the collaborator's quality, network cohesion and expertise similarity have opposite effects on a designer's creative outstanding performance. Thus the collaborator's quality is a moderator that helps us reconcile this seeming puzzle: greater network cohesion and expertise similarity with star collaborators both have positive effects on a focal designer's emergence as star, but in the case of non-star collaborators we observe negative effects under the same conditions. We claim that the primary reason for these contrasting effects is, once again, the significant difference in tacit (design) knowledge between stars and non-stars. In star collaborations, the designers' strong network cohesion provides convergent social forces while their high expertise similarity provides absorptive capacity; these outcomes are conducive to superior knowledge transfer, which ultimately fosters outstanding creative performance. A focal designer and a non-star collaborator, in contrast, differ little in terms of experience or talent. As a result, high social cohesion and high expertise similarity lead instead to "group thinking" and redundant sources of information, which are both well known to have negative effects on creative performance.

Our results speak directly to the literature on knowledge transfer (Boland & Tenkasi 1995; Argote et al. 2003). Unlike previous research that focuses on procedures to facilitate such transfers, our study focuses on the knowledge provider's *quality* as a contingency that well explains the varying effectiveness of knowledge transfer. Adopting that perspective enables us to reconcile conflicting results (reported in the extant literature) regarding the effects of network structure and expertise similarity on knowledge transfer in interpersonal collaborations (Burt 2004, Fleming, Mingo, et al. 2007, Groysberg et al. 2011, Reagans and McEvily 2003, Sosa 2011, Tortoriello et al. 2015).

From an empirical standpoint, examining the effects of interpersonal collaboration is a challenging exercise because the focal designer's quality could affect not only her likelihood of engaging in a star collaboration but also the likelihood of emerging as a star herself. An ideal empirical setting would involve pairs of twins being randomly assigned to collaborate with stars and non-stars. Of course, that type of data is not easily available; hence we resort to "constructing" such a database by way of a coarsened exact matching approach (Iacus et al. 2011). Using the sample so constructed to test our baseline hypothesis isolates as much as possible the effects of collaborating with a star from possible factors that could also drive the tie formation with a star. We also employ a DID framework to show that star collaboration does lead to a significant increase in the focal designer's post-collaboration productivity, which is in line with the design knowledge transfer mechanism underlying our hypotheses.

This study relies on archival data derived from design patents, and that approach imposes several limitations common to all research based on patent activity. For example, the findings reported here are based on successful collaborations—those resulting in patents that are actually granted. However, designer–star collaborations may sometimes fail. Yet that should not jeopardize our conclusions because this paper's focus is on how collaboration affects exceptional outcomes (i.e., becoming a star). Furthermore, by evaluating the work of designers in terms of the USPTO's consistent standards, we ensure that our definition of a "star" is likewise consistent and hence that our comparisons (and conclusions) across time are justified. Finally, we note that establishing causality with our empirical method is complicated not by sorting or double selection per se but rather by the possibility of unobserved characteristics driving both the exposure to and the outcome of the "treatment" (becoming a star). We acknowledge that the nature of our data does not allow us to remove all doubts unequivocally; nevertheless, our robustness checks offer consistent evidence that the effect of a star collaboration should not be viewed as spurious.

Our focus on the phenomenon of star emergence raises intriguing questions that can spark additional research. For instance: Given that the achievement of star status is both desirable and challenging, how can that status be sustained? What factors might accelerate a decline from stardom? Future work that explores these and other related questions would advance our knowledge about the topic of stardom.

In reviewing the lives of eminent philosophers from ancient China and Greece, Collins (1998) shows 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 patent data set as a means to quantify the effects of collaborating with a star designer and thus to explain the phenomenon of star emergence. A unique aspect of this study is our finding that knowledge transfer in such collaborations should be considered while accounting also for the quality of collaborators. A firm could use these results when seeking to improve its cultivation of future stars, thereby increasing its own design competitiveness and perhaps beneficially shifting the firm's focus and direction.

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