Do Gurus Breed Gurus?
The Role of Knowledge and Social Effects in the Emergence of Design Gurus
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Do gurus breed gurus?  
The role of knowledge and social effects in the emergence of design gurus

Despite being rare, gurus make disproportionately influential contributions to their fields. Hence understanding their emergence is critical. Yet our knowledge about the phenomenon is limited. This paper studies the role of collaboration in the emergence of gurus among designers—namely, how a focal designer’s chances of becoming a design guru are affected by collaborating with design gurus. We find that collaborating with a guru makes emergence much more likely than does collaborating with other non-gurus, or not collaborating at all. We establish two conduits for this effect of guru collaboration: transfer of knowledge and sharing of attention. First, we present evidence that guru collaborations facilitate the transfer of (tacit) knowledge and thus increase the likelihood of a guru’s emergence. Second, we document a novel social aspect of collaborating with a guru: doing so helps the focal designer emerge as a guru by profiting from the attention paid by others to that guru. We test our predictions via event history analysis performed on a large longitudinal data set consisting of all designers who were granted a design patent in the United States from 1975 through 2005.

Keywords: emergence of gurus, design patent, collaboration, knowledge transfer, social effect

INTRODUCTION

How do creative geniuses—also known as “gurus”—emerge? In particular, does interacting with a guru affect one’s emergence as a guru? If so, then exactly how? Consider Michelangelo and Picasso: each is regarded as an exceptional artist who shaped the artistic understanding of his era, but their formative years proceeded in decidedly different fashions. Michelangelo was discovered as an adolescent by the Medici family, which ruled Florence, and spent his youth as an apprentice to the greatest artists of the time. His masterpieces were the culmination of the Renaissance art tradition (Clément, 1892). Picasso was taught basic painting techniques by his father and later joined the foremost Spanish art school, the Royal Academy of San Fernando in Madrid. In contrast to Michelangelo, however, Picasso could not adjust to that institution’s formal way of learning and quickly dropped out to follow his own artistic inclinations. His masterpieces ran counter to the prevailing traditions and were instrumental in creating expressionism and especially cubism (Gardner, 1993). In short, Michelangelo learned from gurus and eventually became one himself; Picasso relied on his own creative instincts to become a guru. There are two questions that arise in this context. First, is an individual’s path to “guru-ness” helped (or perhaps
harmed) by working with other gurus? Second, how does interacting with an established guru affect the prospective guru?

Gurus have long been a topic of scholarly research. In his 1790 *Critique of Judgment*, the German philosopher Immanuel Kant stated that geniuses must be both “original” and “exemplary” (i.e., influential; Kant, 1952)—a social perspective that we find especially suitable for the purposes of this study. The positive effects of such gurus (a.k.a. stars, elites, experts) have been extensively documented and studied (Azoulay, Graff Zivin & Wang, 2010; Ernst, Leptien & Vitt, 2000; Hinds, Patterson & Pfeffer, 2001; Lotka, 1926; Narin & Breitzman, 1995; Price, 1976; Zucker, Darby & Brewer, 1988). They contribute disproportionately to the advancement of knowledge in their respective domains and contribute valuable knowledge assets to the organizations with which they are associated. Yet this outsized effect is in sharp contrast to our lack of knowledge about their emergence.

A number of studies focus on an inventor’s characteristics—such as mind and personality—in seeking to unveil the ethereal sources of unusual creativity (Schaefer, 1969; Simonton, 2008). Others have focused on the contextual circumstances of the inventor. The seminal case studies of Jewkes, Sawers, and Stillerman (1958) attribute the majority of “breakthrough” inventions to individual inventors; the authors claim that great scientists are inevitably “lone wolves” (17–28). Because they are free of organizational constraints, independent inventors are able to generate radical and system-originating inventions (Hughes, 2004); such inventors do not contend for status and are not held back by interpersonal considerations or communication breakdowns (Diehl & Stroebe, 1987). However, all that research is contradicted by the well-documented benefits of collaboration in various contexts (Cummings, 2004; Groysberg & Lee, 2008; Singh & Fleming, 2010). For instance, Simonton (2009: 135) points out that “the concept of lone genius is one of those misguided myths” and argues that a guru is “nothing more than a mouthpiece for the large zeitgeist”.
In this paper we focus on knowledge and social factors in the development of gurus. Taking the absence of collaboration as our baseline, we ask whether collaborator quality is instrumental in guru emergence. We therefore start by investigating whether, from the non-guru’s perspective, collaborating with gurus is more beneficial than is working with other non-gurus or not collaborating at all. Second, we explore the mechanisms by which collaborating with a guru effects its benefits. Two main mechanisms are salient. Gurus may benefit their collaborators by sharing knowledge, especially tacit knowledge. At the same time, gurus may bestow social benefits on their collaborators by drawing critical attention to the non-guru’s work.

We test our theoretical arguments in the empirical setting of industrial design. Design capabilities have become crucial for companies as they seek to gain a competitive advantage, and the designer’s role has evolved from mere style concerns to more consequential aspects, which include product and process engineering as well as field support for customers (Verganti, 2010). As a result, firms that emphasize design-inspired innovation have been more successful at generating growth (Utterback et al., 2006). Design gurus have become celebrities in their own right with a particular value for the firms that employ them (BBC, 2013; Miller, 2013). Our data on the design industry comes from the design patent database of the US Patent and Trademark Office (USPTO, 2012)—whereas previous studies have focused primarily on utility patents. Under US patent law, utility patents and design patents are two distinct categories of legal entities: the former protect the way an item works; the latter protects how it looks. We mined and processed design patent data for the period 1975—2010 to examine the careers of individual designers. Adopting Kant’s (1952) “social” perspective on the notion of guru, we identified 14,932 gurus based on their (design) inventions and influence from a pool of 215,353 designers.

We find that designers who collaborate with gurus are more likely to emerge as gurus later on than if they collaborate with non-gurus or remain a lone (non-collaborating) designer. We confirm the existence of two conduits for this effect: knowledge transfer and attention sharing. The knowledge transfer dynamic is characterized by three contingencies. In particular, our results indicate that a guru’s number of
collaborators is inversely related to the focal designer’s likelihood of emerging as a guru, that repeated collaborations with a guru increase the benefits accruing to the focal designer, and that more expertise overlap with a guru is beneficial. Beyond the effects of knowledge transfer, attention sharing can increase the likelihood that designers working with a guru will themselves achieve guru status. The ideas of a guru engender substantial critical attention, which can spill over to collaborators and thereby result in increased attention to the focal designer.

LITERATURE REVIEW

Creativity is a crucial source of innovation and an integral part of human life. Scholars have scrutinized both the dispositional and the contextual (e.g., organizational) antecedents of creativity. A topic frequently addressed is the role of collaboration in creativity. Table 1 arranges some representative studies on the role of collaboration in innovation in terms of two criteria. The table’s horizontal axis distinguishes between collaboration in general and collaboration with outstanding innovators (gurus). The vertical axis accounts for whether it is average or rather superior creative performance being considered. This taxonomy gives examples of previous research in three quadrants; the fourth (lower right) quadrant corresponds to the gap that our paper aims to fill.

Most of the literature deals with the effects of collaborators on average creative performance—such as the average quality of ideas or the average number of ideas generated—and does not distinguish among individual collaborators’ prominence or status. This body of work focuses mainly on network properties in order to identify the effects of collaboration’s structural characteristics on average creative performance. Fleming, Mingo, and Chen (2007), for example, demonstrate a paradoxical consequence of collaborative brokerage, which can help generate an idea yet hamper its diffusion. Uzzi and Spiro (2005) examine the network of creative artists associated with Broadway musicals and show that a cohesive network is positively associated with better performance of the production. Sosa (2011) finds that the
content and structural attributes of a dyadic relationship help determine the generation of potentially creative ideas. Tortoriello and Krackhardt (2010) find that bridging ties have a positive impact on individual’s innovative performance if such ties are Simmelian (i.e. they form strongly connected cliques).

Another line of research has shown the effect of high-caliber collaborators on the average performance of collaborator. Coauthors of a “superstar” scientist exhibit a 5–10% decline in their publication rates if that star scientist dies suddenly (Azoulay et al., 2010). A converse effect is studied by Waldinger (2010), who shows that increasing the quality of a university’s faculty has a significant and positive effect on the outcomes of that university’s research students.

All these studies focus on average performance as the key variable of interest. However, an emergent stream of research on creativity explores breakthroughs rather than the average invention (Girotra, Terwiesch, & Ulrich, 2010; Singh & Fleming, 2010; Taylor & Greve, 2006). Especially when attempting to foster innovation, most companies prefer to find the “single best” idea rather than several mediocre ones (Terwiesch & Ulrich, 2009). Breakthrough inventions provide a unique competitive advantage and foster core competences and unique problem-solving skills (Ahuja & Lampert, 2001). Singh and Fleming (2010) find that individuals working alone are less likely to achieve breakthrough patents and more likely to patent relatively poor ideas. Girotra, Terwiesch, and Ulrich (2010) demonstrate the importance of team structure for generating and identifying the best idea. However, even this literature stream does not distinguish collaborators based on their prominence; instead, it views collaboration as a homogeneous construct.

When previous research on collaborative innovation is classified along the lines of Table 1, a significant gap in the literature becomes apparent. Insufficient attention has been paid to the question of how exceptional collaborators affect the likelihood of achieving exceptional creative results. By classifying

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1 Although not in the context of creativity, Groysberg and Lee (2008) explore whether the performance of financial “stars” resides mainly in their talents or in the firm for which they work. In other words: How much of a star’s knowledge is portable across organizations? These authors find that higher-quality colleagues help to maintain the stellar performance of top analysts.
collaborators in terms of their prominence, we depart from traditional network research that emphasizes structure (Burt, 1992; Granovetter, 1973). We address the less well-documented issue of tie characteristics (Cross & Cummings, 2004; Oh, Chung, & Labianca, 2004) by studying collaborators of different standing. In this paper we study the effects of direct ties as a function of their quality; in particular, we show that \textit{ties to gurus} and \textit{ties to non-gurus} make significantly different contributions to the likelihood of a guru’s emergence.

We also contribute to the literature on interpersonal collaboration by disentangling the social effect of collaborations from their knowledge transfer effect. The literature on knowledge transfer has identified learning as the main mechanism by which performance is affected in the typical collaborative setting and has therefore focused primarily on those contingencies that either facilitate or hinder the transfer process (Reagans & McEvily, 2003; Winter & Szulanski, 2001; Zander & Kogut, 1995). In this paper we posit that another factor may well affect performance in settings that involve interpersonal collaboration: the relative social prominence of collaborators. We confirm its importance in the emergence of a focal designer as a guru. When characterizing collaboration in the context of innovation, we must consider social effects in conjunction with the effects of knowledge transfer.

**THEORY AND HYPOTHESES**

Why should collaborating with a guru matter, and why should it be more beneficial than collaborating with a non-guru? Two main arguments can be made. The first centers on the notion of (tacit) knowledge transfer. Much of design knowledge is tacit: a feel for avant-garde trends in design, a unique approach to style, an appreciation of beauty, a talent for illustration. Tacit knowledge cannot be codified and is difficult to articulate. As a result, such knowledge is not easily transferred (Teece, 1977; Zander & Kogut, 1995) and can truly be acquired only through experience (Nelson & Winter, 1982; von Hippel, 1994). Scholars have therefore argued that up-close observation and emulation are the main mechanisms by which tacit knowledge is passed on (Hamel, 1991). Design gurus have developed extensive (tacit) knowledge in their fields—considerably more so than other designers. Hence collaborating with a guru
should be a viable means for a less experienced or accomplished designer to tap into (and profit from) the guru’s superior knowledge.

The second mechanism by which collaboration with a guru benefits the focal designer is through the guru’s disproportionate social capital being shared with the collaborating designer. Gurus are “accorded high status by those around them, both implicitly and explicitly, both locally and globally” (Groysberg, Polzer & Elfenbein, 2011: 724). Various advantages accrue to high-status individuals, and those advantages are often bestowed on their collaborators (Merton, 1968); examples include increased public attention (Zuckerman, 1967) and opportunities to work with other gurus. Such status effects can lead to a virtuous cycle in which the focal designer’s status is enhanced by these additional resources (Allison & Stewart, 1974; Simcoe & Waguespack, 2011).

In the field of social psychology, Merton (1968) argues that—with regard to similar achievements—gurus receive substantially more credit than their less prominent counterparts. This disproportionate attention has a spillover effect on those who collaborate with a guru. An up-and-coming designer can profit directly from that attention, as when building critical acclaim from other designers or even when enjoying such advantages as the goodwill of contest judges. These perquisites may have lasting benefits because they endure and are even amplified over time to yield what is referred to as “cumulative advantage” (Allison & Stewart, 1974; Merton, 1968; Price, 1976). In contrast, the work of designers collaborating with other non-gurus does not receive any special attention and so the collaboration’s output cannot be leveraged to any comparable extent.

So far we have argued for the advantages of collaborating with a guru rather than a non-guru. The dynamics of (tacit) knowledge transfer and (overt) critical attention are just as applicable when arguing that the benefits of collaboration per se exceed those of noncollaboration. So using the absence of collaboration as our base case, we formalize the preceding considerations in our first hypothesis as follows
**Hypothesis 1:** A designer is more likely to become a guru by collaborating with a guru than by collaborating with a non-guru or not collaborating at all.

Once we accept the notion that collaboration with a guru enables the designer to access advantageous knowledge and social capital, the next question becomes: Do these effects follow equally from all gurus? Are there some guru characteristics that prove to be more beneficial? Addressing these questions will allow us to shed more light on the contingencies of the guru collaboration effect.

More specifically, we first investigate how a guru’s effect on collaborators depends on the number of those collaborators. Gurus have accumulated a large amount of knowledge and are highly respected in their respective domains. In order for this knowledge to benefit their collaborators, it needs to be shared. From a practical standpoint, knowledge transfer imposes a cost on the source (Szulanski, 1996; Winter & Szulanski, 2001): it takes time and effort to impart that knowledge (Reagans & McEvily, 2003). Because gurus face both time and energy constraints, the effects of collaborating with a guru should be greater when the guru has fewer collaborators (Granovetter, 1973; Katona, Zubcsek & Sarvary, 2011). In other words, a guru with more collaborators has less time, on average, that can be devoted to any one of them (French & Raven, 1960) and so less knowledge can be transferred to each collaborator. This “dilution” effect limits the benefits of collaboration and leads to our next hypothesis.

**Hypothesis 2:** A designer is more likely to become a guru by collaborating with a guru who has relatively fewer collaborative ties than by collaborating with one who has relatively more such ties.

Similarity with regard to expertise reflects common knowledge in professional experiences, and common knowledge is expected to facilitate knowledge transfer (Reagans & McEvily, 2003). Hence the closer two collaborators are in the “idea space”, the more likely and effective will be any knowledge transfer between them. On the other hand, if two individuals do not share a common “language” then knowledge transfer between them will be impeded. Findings from the literature on absorptive capacity indicate that
one can more easily acquire new knowledge if it is more closely related to the knowledge one already has (Cohen & Levinthal, 1990). A common basis of similar experiences thus simplifies the exchange of ideas between individuals in the same field. As a result, more “expertise overlap” facilitates the transfer of tacit knowledge. We thus expect that learning from a guru will be more effective when the focal designer shares a common knowledge base with that guru. Indeed, Azoulay et al. (2010) document with respect to scientific research that, the closer a focal scientist’s intellectual space is to that of a “star” in that field, the more the scientist profits from the star’s knowledge. These authors show that the proximity of intellectual background serves as a conduit for knowledge spillover. The implication for guru–designer collaboration is that a greater extent of expertise overlap allows the guru to provide more in-depth advice to the collaborator and also makes the collaborating designer more able to internalize the guru’s knowledge. Formally, we have the following statement.

**Hypothesis 3:** A designer is more likely to become a guru when there is more overlap in the respective areas of expertise with a guru collaborator.

Some network theorists argue that collaboration characterized by weak rather than strong ties is more conducive for creative output (Perry-Smith & Shalley, 2003). Weak ties facilitate the recombination of diverse sources of information and are less likely to be redundant (Burt, 2004). However, their efficacy is based on the assumption of a fairly effortless knowledge flow from source to recipient (Burt, 1992; Granovetter, 1973). In fact, research shows that the transfer of complex tacit knowledge is extremely challenging (Teece, 1977; Zander & Kogut, 1995) and that the ease of such a transfer depends instead on the strength of ties (Hansen, 1999; Uzzi, 1997). Similarly, to produce a work of art necessitates strong ties as well (Becker, 1982). It is therefore reasonable to suppose that effective in-depth learning about design requires strong rather than weak ties.

Close collaboration entails strong ties, which should benefit the transfer of tacit knowledge from gurus to designers. Individuals who collaborate more closely can more easily obtain assistance from each other
because the motivation to be of assistance is greater (Granovetter, 1982). Engaging in close collaboration gives a focal actor the opportunity to seek feedback, and such collaborators are likely to spend more time sharing their experience and knowledge (Hansen, 1999; Marsden & Campbell, 1984, Reagans & McEvily, 2003, Sosa 2011). Such bidirectional interaction and trust afforded by up-close observation and emulation of the “best in class” is crucial for assimilating complex tacit knowledge. Hence we argue that a designer’s close collaboration with a particular guru establishes strong ties and facilitates knowledge transfer from that guru, making it more likely that the designer will emerge as a guru.

**Hypothesis 4:** *A designer is more likely to become a guru by collaborating repeatedly with the same guru than by collaborating with several gurus.*

So far, we have concentrated on knowledge transfers engendered by close collaboration as the main mechanism by which a collaboration with a guru can further the focal designer’s career. Yet there may also be other aspects of such collaboration—in particular, social effects that manifest as a spillover of attention from the guru to the focal designer.

These social effects are driven by two processes. First and foremost, gurus have established a strong reputation and have attained prominence. Collaborators can hugely benefit from that status. A few interviews led Zuckerman (1967) to suggest that, because a Nobel laureate’s work will naturally receive much notice and appraisal by peers, the work of a Nobel laureate’s collaborators will also enjoy enhanced publicity. In the field of engineering, Simcoe and Waguespack (2011) find that technical proposals from high-status authors generate more discussions, and are more likely to be published, than those from less respected authors. Collaboration with a guru can thus serve to advertise a focal designer’s own ideas—an essential component of developing and advancing a new concept (Podolny, 2005: 26). Second, a guru’s positive evaluation lends credibility to the designer since the guru’s endorsement carries more weight in the community than would those of lower-status individuals (Stewart, 2005). An example of this dynamic is given by Azoulay et al. (2010); they show that researchers who collaborate with a more influential star
scientist exhibit steeper declines in citations after that star dies than do those who collaborated with less renowned star scientists (but also deceased).

Thus, the social effects that attendant upon guru collaboration cause the designer to receive not only more attention but also more appreciation. We therefore expect that a designer collaborating with a guru who commands a bigger “attention pool” will have a greater chance of becoming a design guru. This expectation is formalized in our final hypothesis.

**Hypothesis 5:** *A designer is more likely to become a guru by collaborating with a guru who has a larger attention pool than with one who has a smaller attention pool.*

**DATA AND METHODOLOGY**

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. It has been presumed that such a collaboration history, one that includes evaluations for each piece of work, is unavailable in the design industry. Design patent data, however, does 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 for which the patent is granted), and citations to other patents. The rich information embedded in design patent data serves our goals perfectly, especially since the inventions described by patents are one of the few forms of creative output whose documentation is publicly available (Audia & Goncalo, 2007). We obtained our design patent data by “crawling” the website of the US Patent and Trademark Office (USPTO).²

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

³ We have incorporated data from the Technology Assessment and Forecast (TAF) database, which is administered by USPTO’s Patent Technology Monitoring Team (PTMT).
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, 2012). In general terms, a design patent protects the appearance of an item whereas a utility patent protects an item’s functionality. Because design patents focus on innovations in form, not function, the scope of such patents is limited to the “overall ornamental visual impression” (USPTO, 2012). The first design patent was awarded in 1842 to George Bruce for inventing a new font (typeface). In 1879, Auguste Bartholdi was awarded a design patent for the Statue of Liberty’s design.

Although our study is the first to use design patent data on a large scale, 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 individual designers. Second, there is a tradition of using patent data to analyze creativity because that data enables us to quantify creative output (Shalley & Zhou, 2008) and so eases 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 (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 & 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.
Identifying Design Gurus

We define the *popularity index* of a designer at any moment in time by counting the citations received by that designer’s patents in the preceding three-year rolling window. An inventor whose popularity index is in the top 2% of all inventors is considered to be a guru (at the time of measurement). This operationalization of guru-ness 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 (2010) use a 5% cutoff—for both the upper and lower tails of the distribution—when identifying (respectively) breakthrough and poor inventions. With regard to the time window, scholars who study archival data have used windows ranging from three years (Fleming, Mingo & Chen, 2007) to five years (McFayden & Cannella, 2004) when assessing an inventor’s performance. The use of a time window is—in the first place—due to the fact that 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 while setting the cutoffs at 1%, 2%, and at 5% and while using rolling time windows of three, five, and seven years as well as no window at all. These various alternatives do not yield qualitatively different results.

Dependent Variable: Guru’s Emergence As an Event

We define the emergence of a guru—or the transition from designer to guru—as an *event* in the designer’s career. It corresponds to that moment when the designer’s popularity index first attains the 2% threshold. Of the 215,353 designers in our data set, 14,932 (about 6.9%) can be identified as gurus at some point. This percentage is in line with previous research, which has pegged the prevalence of gurus

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4 This proportion is not at odds with our definition of a guru (i.e., an inventor in the top 2% of designers based on their popularity index at a given time). The 6.9% figure represents the average percentage of gurus over all our observations, whereas the 2% figure is the “instantaneous” percentage for any given time.
at values ranging from 0.75% to 10% (Ernst et al., 2000; Groysberg et al., 2011; Narin & Breitzman, 1995; Zucker et al., 1988).

**Independent Variables**

A modest amount of notation helps define our independent variables. In line with the estimation approaches of event history analysis, where the relative order of events matters, we index each patent application date: \( t \in [1, T] \); here \( t \) is an integer and \( T \) is the last instance of a patent application in our data. The total number of designers who have applied for a patent up to time \( t \) is \( N_t \).

**Direct ties.** This variable counts the number of unique collaborators of a focal designer in the past. Following well-established practice, we project the bipartite collaboration network into its unipartite counterpart (Fleming, Mingo & Chen, 2007; Newman, 2001; Uzzi & Spiro, 2005); thus, designers have collaborated or “worked together” if they have applied for a design patent together (Toh & Polidoro, 2013). We use \( H_{it} \) and \( L_{it} \) to denote (respectively) the sets of gurus and non-gurus with which designer \( i \) has worked up to time \( t \). Then the *Direct ties* of designer \( i \) up to time \( t \) is defined as

\[
\text{Direct ties}_{it} = |H_{it} \cup L_{it}|
\]

This variable is used to test for a base effect of collaboration—that is, whether *any* type of collaboration is conducive to a designer becoming a guru.

**Direct ties to gurus.** This variable counts the number of *unique* guru collaborators of a focal designer \( i \) up to time \( t \) and consists of the set \( H_{it} \). The more *Direct ties to gurus* a designer has, the more experiences and benefits that designer has accumulated by working with gurus.

**Direct ties to non-gurus.** Analogously to the previous variable, this is the number of unique non-guru collaborators of a focal designer \( i \) up to time \( t \); this variable consists of the set \( L_{it} \) and is a proxy for the focal designer’s past experiences working with non-gurus. We use it in conjunction with *Direct ties to gurus* to test Hypothesis 1, which posits that a designer benefits more from collaborating with gurus than with non-gurus.
**Guru’s direct ties.** This variable captures the network size of all of the gurus with which a focal designer $i$ has worked. More formally, let $G_{jt}$ be the set of past collaborators of guru $j$ as of time $t$. Then, with respect to a focal designer $i$, we define \(\text{Guru's direct ties}_{it} = |\bigcup_{j \in H_i} G_{jt}|\). This variable is used to examine the effect of the guru’s network size (Hypothesis 2). Since collaboration consumes time and energy, a guru with more collaborators offers fewer benefits (on average) to the focal designer because of the posited dilution effect.

**Expertise overlap with gurus.** We capture the breadth of a designer’s expertise by counting the number of unique classes into which the designer’s patent applications fall (again, up to time $t$). Then expertise overlap is calculated as the number of unique patent classes that subsume *both* the designer’s and the guru’s applications (i.e., their intersection) divided by the number of unique classes related to the focal designer’s applications *only*. This variable is thus a proxy for how similar the guru’s field of expertise is to that of the focal designer; it is bounded by 0 and 1, with higher values indicating more *Expertise overlap with gurus*. We use this variable to test Hypothesis 3.

**Strength of collaborations with gurus.** Although an affective construct would be a good candidate for operationalizing closeness and strength of collaboration (Burt, 1992), the information needed to create such a variable does not appear in archival patent data. So to test Hypothesis 4, we adopt a strength-of-tie measure that is based on observations of repeated collaboration in an organizational context (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 guru(s). Formally, we set $c_{ijt_0} = 1$ if designers $i$ and $j$ collaborate exactly at time $t_0$. Then we define

\[
\text{Strength of collaborations with gurus}_{it} = \frac{\sum_{t_0=1}^{t-1} \sum_{j \in H_i} c_{ijt_0}}{|H_i|}.
\]

The value of this measure is 1 when the designer collaborates with a particular guru exactly once; the value increases as the focal designer works on subsequent projects with the same guru.
**Guru’s attention pool.** The strength of a guru’s social effect is conceptualized as the extent to which the focal designer becomes better known (within the relevant design community) by collaborating with that guru. In order to measure this effect, we count the number of designers citing the guru’s patents in their own patent applications. We may suppose that a guru whose patents are cited by more designers has accumulated more attention; that is, a more highly cited guru has a larger “pool” of followers. A guru with a larger following can bestow more social attention on collaborators than can a guru with a smaller following. We therefore define the *Guru’s attention pool* as the number of individuals who have, up to time $t$, cited the guru’s patents.

Let $p_f$ be a patent in the set $P_f$ of patents granted to a focal guru $f$. We define $c_f$ as a *citing* patent if $p_f$ is in the citation list of $c_f$. We use $C_f$ to denote the set of citing patents, such that any $c_f \in C_f$ cites some $p_f \in P_f$. Denote by $A_{fc}$ the set of coauthors on patent $c_f$. As usual, subscript $t$ implies “up to time $t$”. Then we formally define the attention pool of a guru $f$ up to time $t$ as *Guru's attention pool*$_{ft} = \sum_{c_f \in C_f} |A_{fc}|$. (In the “Robustness Checks” section we construct some alternative proxies of the guru’s attention pool.)

**Control Variables**

Our aim in this article is to establish whether working with a guru helps transform a designer into a guru—and, if so, to identify the relevant contingencies and underlying mechanisms. It is typical for a designer who collaborates with a guru to collaborate also with non-gurus; hence we need to control for characteristics of those non-gurus. The following variables are defined analogously as for gurus: *Non-guru’s direct ties, Expertise overlap with non-gurus, Strength of collaborations with non-gurus*, and *Non-guru’s attention pool*. All these serve as control variables since we make no theoretical claims about their effects.

In isolating the effects of gurus, it is important to address two critical confounding effects: the innate capabilities of designers and the antecedents of tie formation with a guru. The designer’s innate capability
and past experience figure largely in predicting individual creativity and, ultimately, career success (Fleming, Mingo & Chen, 2007; Reagans & McEvily, 2003; Simonton, 2000). Those characteristics may also determine how ties with a guru are formed. One can reasonably expect that a guru, when selecting collaborators, favors capable individuals over less capable ones (Lee, 2010). In a case study of Nobel Prize winners, laureates indicated that they were highly selective not only when choosing a mentor early in their careers but also when choosing their students once their careers were well established (Zuckerman, 1967). Unfortunately, a large-scale study such as ours has no hope of measuring innate capability in a manner favored by social psychologists—which would require data indicative of intrinsic interest (Eisenberger & Cameron, 1996), affective states (Amabile, Barsade, Mueller & Staw, 2005), and/or group interactions (Hirst, Van Knippenberg & Zhou, 2009). Hence we control for heterogeneity in the creative abilities of designers by constructing four variables as follows.

**Assignee past patents.** Assignee is usually the organization that the designer is associated and also the organization that has the patent ownership. 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 contemporaneous R&D or 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 to calculate that organization’s cumulative number of patents up to time \( t \).

**Mobility.** The number of organizations with which an individual has been associated is strongly correlated with that individual’s experience (Fujiwara-Greve & Greve, 2000; Mincer & 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 that designer’s patents awarded until time \( t \). This variable captures the designer’s experience in working with different organizations.
**Class diversity.** The USPTO classifies design patents in terms of their intended use (USPTO, 2012). For instance, designs of lights are in class D26 (“lighting”). Altogether there are 33 classes, and the designs in each of the classes require substantially different skill sets to produce. Audia and Goncalo (2007) show 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 in which a designer has secured patents can serve as a proxy for capability. Hence our *Class diversity* variable is a count of the number of unique classes 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 be the result of 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. This information can be gleaned from the patent documents that make up our data set.

**Selectivity.** In addition to introducing control variables to address individual differences in capabilities, we follow a tradition in the related literature by applying Heckman’s (1979) two-stage model. When studying the career imprints of academic entrepreneurs, Azoulay, Liu, and Stuart (2009) use this model to explore the matching or “partial selection” between recent graduates and their postdoctoral mentors (the first-stage estimation) and the effect that mentors have on those graduates (the second-stage estimation) while controlling for the partial selection. In another study, Fleming, Mingo, and Chen (2007) use a Heckman two-stage model to address selection bias: the first stage estimates the probability of an invention’s involving at least one new combination of subclasses; the second stage estimates—
conditional on the existence of such a combination—how often it appears in subsequent patent applications.

As described under “Statistical Approach” the second stage of our estimation employs a Cox model. We apply Lee’s (1983) generalization of Heckman’s (1979) two-stage method by estimating a selectivity model in the first stage and then entering the selectivity variable in the second stage as an instrument (Mitsuhashi & Greve, 2009; Rao, Greve & Davis, 2001). More specifically, we estimate a logit model in the first stage by regressing an indicator for guru collaboration (the dependent variable) against a number of independent variables: Time duration since last patent, Total number of past collaborators, Location diversity, Class diversity, and Mobility. Note that the variable Time duration since last patent is excluded from the second stage to enable identification of our model. (Using other exclusion variables, such as First year that a designer starts to patent and Team size of the patent’s collaborators, did not change our results.)

**Patent stock year.** For each year, this variable counts the number of total patent applications in each class. The number of patents applied for (and granted) has increased over the years (Trajtenberg, 1990); it is therefore important—especially in light of our interest in the social effects of collaborators (the attention pool variable)—to control for any underlying trend in the number of patents and citations. In doing so we differentiate between patent classes, since there is variation among classes for different years.

**Cohort.** This is a dummy variable used to control for when a designer begins to file patents. For each designer, it indicates whether the designer first patented before 1986 or rather which one of the subsequent five-year intervals during the 1986–2005 period.

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Table 2 gives the descriptive statistics and correlations for all variables used in our analysis.

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5 Following previous studies (Mitsuhashi & Greve, 2009; Rao et al., 2001), we use a logit model in the first stage; however, all our hypotheses are supported when we use a probit model instead.
ANALYSIS AND RESULTS

Statistical Approach

Most previous empirical studies that use patent data to examine creativity have focused on the number of new patents generated, the number of subclass combinations created, or the number of citations received (Audia & Goncalo, 2007; Fleming, Mingo & Chen, 2007; Lee, 2010; Singh, 2005). However, since we are interested not in a designer’s creative output but rather in the probability of that designer becoming a guru, the common practice of using a panel regression with a count-type dependent variable is not applicable. We therefore test our hypotheses using event history analysis. Such analysis allows us to model precisely the relative likelihood of an event (i.e., the emergence of designer as a guru) over a specific time span while taking into account the difference between censored and uncensored cases (Blossfeld & Rohwer, 1995). Event history analysis also allows us to study right-censored observations, which occur when information about the event of interest is not complete because the sample data is available only up to a certain time—as when a designer has not become a guru by the end of our observation window yet might become one at a later date.

As is customary in event history analysis, we estimate Cox proportional hazard models on survival time data via a maximum likelihood method (Cox, 1972). The “hazard” here is the probability that a designer will become a guru during the time window of observation (1986–2005). In our study, observations include all designers who have been awarded a design patent and are thus “at risk” of becoming a guru. For estimation purposes, we use the *stcox* command in Stata 12.0.

Testing the Baseline Hypothesis

A first examination of the data provides preliminary evidence that there is a higher percentage of gurus among designers who have collaborated with gurus (Table 3). We find that, among those designers who collaborated with gurus, 5,429 (23.67%) later emerge as gurus themselves. By way of comparison, only 5.93% (resp., 3.96%) of the designers in our data set emerge as gurus after collaborating only with non-gurus (resp., when always working alone).
As a formal test of our hypotheses, Table 4 reports the results of our event history analysis. Model 1 tests the baseline argument that collaboration in general (i.e., not just collaboration with a guru) increases the chances of becoming a guru. Note that we offered no hypothesis regarding this effect because it serves only a comparative purpose. Our results reveal a positive and significant effect for all the controls that relate to a designer’s base capability—in particular, for the assignee extant stock of patents, the designer’s mobility, and all diversity measures. The selectivity control is also significant, which indicates that designer–guru matching is a crucial antecedent of performance.

With regard to the baseline effect of collaboration itself, under Model 1 there is a positive and significant coefficient for Designer’s direct ties (0.329, \( p < .001 \)). This result replicates (and slightly extends) previous findings associated with the benefits of collaboration: not only does collaboration facilitate learning and generate new ideas (Fleming, Mingo & Chen, 2007), including breakthrough ideas (Singh & Fleming, 2010), it is also instrumental in the emergence of designers as gurus. The effect of collaboration on “guru-proneness” is notable: Model 1 implies that, at one standard deviation above the mean, the (logged) direct ties variable makes a designer 4.3 times \( (e^{0.71+0.76} = 4.3) \) more likely to emerge as a guru.

Model 2 tests Hypothesis 1 (H1), which claims advantages of guru collaboration in comparison with non-guru collaboration or with no collaboration at all. First, and consistently with Model 1, the coefficients for both Direct ties to gurus (0.613, \( p < .001 \)) and Direct ties to non-gurus (0.226, \( p < .001 \)) are positive and significant; these results imply that any type of collaboration is preferable to no collaboration at all (the omitted case). We can further interpret the relative effect of collaborating with gurus versus non-gurus by examining their respective hazard ratios. A one-unit increase in (the natural logarithm, Ln, of) Direct ties
to gurus makes the focal designer 1.85 times ($e^{0.613} = 1.85$) more likely to emerge as a guru as compared with a designer who has no ties. Similarly, a one-unit increase in Direct ties to non-gurus (Ln) yields a corresponding factor of $e^{0.226} = 1.25$. The effect of collaborating with gurus rather than with non-gurus increases the hazard rate by 1.47 times (1.85/1.25 = 1.47), and the difference between these effects is statistically significant ($p < .001$). Therefore, Hypothesis 1 is fully supported. In terms of increasing a designer’s prominence, the effect of collaborations are clearly ordered, greatest to least, from guru collaboration to non-guru collaboration to no collaboration at all.

In addition to the effects of Direct ties to gurus and Direct ties to non-gurus, we can analyze marginal effects. Thus we analyze the effect of the first, second, and third collaborators on the likelihood of guru’s emergence. The designer’s first guru collaboration increases the chance of emergence by 44% over the case of having no guru collaborator (i.e., having an average mix of non-guru collaborators and no collaborators). This value declines to 24% when we consider the marginal effect of the second guru collaboration—that is, beyond the effect of the first one. The marginal effect of the third guru collaboration (beyond the effect of the second) is only 16%. The respective effects for non-guru collaborations (32%, 18%, and 12%) exhibit the same pattern but at a lower absolute level. In sum, the marginal effects of guru collaborations are greater than those of non-guru collaborations, and both effects exhibit a pattern of diminishing returns (Figure 1).

**Testing for Knowledge Transfer Effects**

Model 3 tests Hypothesis 2, which argues that the focal designer’s likelihood of emerging as a guru is decreasing in the collaborating guru’s number of collaborators. Model 3 shows a negative and highly significant effect for Guru’s direct ties ($-0.017, p < .001$), in line with H2. This finding is consistent with the literature, which has found that the bigger a person’s network, the less time and effort that person
devotes to each contact in the network (French & Raven, 1960; Granovetter, 1973; Katona et al., 2011). Thus the dilution effect due to a greater number of guru ties hinders that guru’s knowledge transfer to the focal designer.

Model 4 incorporates dyadic measures of expertise overlap that apply to the focal designer and the collaborators of that designer. The coefficient for Expertise overlap with guru is positive and highly significant (0.369, \( p < .001 \)), so Hypothesis 3 is supported. The results indicate that expertise overlap between a focal designer and collaborating guru is beneficial; in particular, overlap that facilitates common understanding increases the efficiency of knowledge transfer. It is interesting that the coefficient of Expertise overlap with non-guru is negative (and also highly significant; \( -0.413, \ p < .001 \)), which implies that an overlap in the knowledge of a non-guru and the focal designer is actually detrimental. This may indicate that knowledge transfer between non-guru designers is of little importance for the focal designer’s emergence as guru and hence that secondary mechanisms prevail—for instance, an outside audience’s blurred perception of the respective designers’ contributions.

Model 5 tests Hypothesis 4, which posits that repeated collaborations with gurus are beneficial for the designer’s emergence as a guru. It shows a positive and significant coefficient for Strength of collaboration with gurus (0.17, \( p < .001 \)), which supports H4. Thus a designer who works repeatedly and closely with the same guru is more likely to become a guru than are designers who establish collaborations with a series of new gurus. The result accords with arguments from social network theory that strong ties are preferable for transferring tacit knowledge (Hansen 1999, Reagans & McEvily 2003).

It is noteworthy that all the models testing for knowledge transfer effects indicate that collaborating with gurus has a greater impact than collaborating with non-gurus; moreover, the difference between the relevant coefficients is highly significant (\( p < .001 \)). This finding suggests that there exists an additional mechanism underlying the differential effects between guru and non-guru collaborations.
Testing for Attention Effects

Hypothesis 5 postulates that collaborating with gurus who have a larger attention pool increases the chances of the focal designer emerging as a guru. In support of this hypothesis, Model 6 shows that the Guru’s attention pool is positive and highly significant (0.001, \( p < .001 \)).

Model 6 lends evidence to our argument that understanding how guru collaboration helps a designer requires that we look beyond knowledge transfer mechanisms and examine attention spillover. Toward that end, Model 6 suggests that Guru’s attention pool mediates the relationship between guru collaboratioinal advantages and the focal designer’s emergence as a guru. In order to establish empirically such a mediation effect, we undertake a counterfactual analysis in the proportional hazard model (Lange & Hansen, 2011; VanderWeele, 2011). This method decomposes the total difference in hazards of becoming guru as the sum of direct and indirect effects on the hazard scale. The direct effect is the change in hazard resulting from changes in the level of the exposure variable, which is the advantage of guru collaboration (i.e., the difference between Direct ties to gurus and Direct ties to non-gurus) when the mediator remains constant; the indirect effect is the change in hazard resulting from changes in the level of the mediator variable, which is Guru’s attention pool, when the exposure variable is kept constant. All other control variables are treated as covariates. The framework for this counterfactual analysis is presented in Figure 2.

We follow the approach described by VanderWeele (2011), who applies the framework proposed by Baron and Kenny (1986) to proportional hazard models. We obtain the coefficient for the exposure variable (the advantage of guru collaboration, denoted \( \gamma_1 \) in Figure 2) as well as the coefficient for the mediator variable (Guru’s attention pool, denoted \( \gamma_2 \) in the figure). In a separate linear model (Lange & Hansen, 2011), we obtain the coefficient that captures the relationship between the exposure variable and the mediator variable (\( \beta_1 \) in Figure 2). According to the counterfactual framework, the direct effect is \( \gamma_1 \)
and the indirect effect is obtained (via the product method) as $\beta_1 y_2$. If this indirect effect is significant then we have empirical evidence of mediation.

To compute the significance level of the indirect effect, we divide $\beta_1 y_2$ by its standard error; that ratio is then compared to the significance level of a standard normal distribution. We use the standard error formulas proposed by Arolan (1947) together with our product method and find that mediation is indeed highly significant ($p < .001$). We can also calculate the extent of mediation as the ratio of indirect effect to total effect. Our results indicate that a substantial portion—28%—of the probability that the focal designer will emerge as a guru is mediated by the collaborating guru’s social effect. All coefficients and standard errors for this mediation analysis are obtained by bootstrapping.

**ROBUSTNESS CHECKS**

To explore the range of conditions under which our claims hold, we conduct extensive robustness analyses. In particular, we check on alternative ways of identifying design gurus and of measuring the social attention pool of collaboration.

In our main analysis, a guru 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 the data set. Our robustness tests consist of systematically varying 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 compare results under cutoff values of 1%, 2%, and 5% for the popularity index. Second, we evaluate the effect of replacing our three-year time window with a five-year and also with a seven-year window. In addition, we check the results when a nonrolling time window is used (i.e., one that extends back to the start of our observation period). The tests show that all of our hypotheses and claims are robust to these variations in the definition of a guru.

The concept of an attention pool aims to capture the amount of heightened attention that a guru attracts and may, in turn, bestow on the collaborating designer. In the main text we adopted a definition of this
transfer potential that was based on all past citers of the guru’s work. However, the attention pool’s effect may depend not only on the guru’s network but also on the designer’s own pre-collaboration network. Therefore, we test our hypotheses when considering only the additions to the designer’s attention network that result from collaborating with a guru. All our hypotheses—and in particular H5, which addresses the social effects of attention transfer—are supported when this alternative attention pool variable is employed.

**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 distinguish among those products. An article’s design aspects have therefore been gaining in importance, a trend confirmed by many comments in the business press (BBC, 2013; Miller, 2013). The field of product design is one in which the guru’s role figures prominently. In categories as varied as clothing, cars, furniture, computers, and communications equipment, design gurus have become household names; in fact, they exert considerable influence over how entire industries conceive their next-generation products. But how do gurus arise? Can a company groom them? Could exposing young talent to established gurus be detrimental? We have remarkably little understanding of what factors influence the emergence of gurus in general, let alone as regards the creative aspects of an industry’s products. As one of the first studies to use a large-scale, longitudinal database of design patents, this paper offers insights into the emergence of gurus in the field of creative design.

With respect to a designer’s emergence as a guru, we contribute to a growing stream of studies in creativity research that aim to understand the drivers of superior as opposed to average performance (Ahuja & Lampert, 2001; Girotra et al., 2010; Singh & Fleming, 2010; Terwiesch & Ulrich, 2009). However, contrary to previous work in this area that adopts the idea as the unit of analysis and explores the emergence of breakthrough ideas, our study focuses on the individual to uncover the myth behind the emergence of a designer as a guru.
With respect to the role of collaboration in the emergence of design gurus, our baseline result distinguishes among collaborators based on their standing in the design community. We show that—far from being equally beneficial—guru collaborators are considerably more instrumental (than are non-guru collaborators) in a designer’s elevation to guru status. This finding is in line with social resource theory, which suggests that those with higher status tend to control desirable resources and that ties to such individuals can therefore be advantageous (Lin, 1999). Our approach of focusing on the collaborator’s relative prominence departs from social network studies and their emphasis on the structure and content of collaborative networks (Cross & Cummings, 2004; Reagans & McEvily, 2003; Sosa, 2011; Tortoriello, Reagans, & McEvily, 2012; Uzzi & Spiro, 2005).

We have identified two mechanisms that underlie the transformation from designer to guru: knowledge transfer and social attention sharing. With regard to the first mechanism, we examine three contingencies. We find that a guru’s network size has a negative effect on the emergence of the focal designer as a guru. This result is consistent with the widely held notions that imparting knowledge requires time and effort from the source of the transfer process (Reagans & McEvily, 2003) and that an increased number of collaborations dilutes the guru’s limited resources (French & Raven, 1960; Granovetter, 1973).

As a second contingency, we find that greater expertise overlap with a guru has a positive effect on the focal designer’s likelihood of emergence. Being intellectually closer to a guru collaborator facilitates the flow of in-depth knowledge because in that case the focal designer is better positioned to integrate such information into her current stock of knowledge. Consistent with this finding, Azoulay et al. (2010) find that a star’s sudden death has a lasting negative effect on the publication rate of her collaborator—and especially when the two are more proximate in idea space. A somewhat unexpected result of our own research is that a higher expertise overlap with non-guru collaborators actually has a negative effect on the focal designer’s career; collaboration with people of similar standing may stifle creativity and possibly blur that designer’s identity. These contrary roles played by expertise overlap in the case of guru versus non-guru collaborations warrant further investigation in future studies.
The third contingency concerns the effect of tie strength when collaborating with a guru. We have discovered that strong ties between a guru and a designer make repeated interactions especially beneficial for the focal designer—perhaps because the process of attaining superior performance, *a fortiori* becoming a guru, requires up-close observation and emulation. Our findings support results in the literature indicating that the strength of interpersonal ties eases knowledge transfer (Hansen, 1999; Reagans & McEvily, 2003; Uzzi, 1997) and can facilitate knowledge creation or the generation of creative ideas (McFayden, Semadeni, & Cannella, 2009; Sosa, 2011; Tortoriello & Krackhardt, 2010).

Going beyond the knowledge transfer dynamic, we propose a link that has not been addressed in the literature on interpersonal collaboration: the social effects of guru collaborators. Our results show that attention transfer from guru to a collaborating designer is a key mechanism by which the collaboration effects its benefits. A guru has accumulated considerable attention from other designers and can use it to help collaborators. Our conceptualizing of social attention is a contribution in its own right because we employ the guru’s citation network in a novel way to capture that guru’s social attention pool. Whereas past literature used patent citations as a proxy for knowledge flow (Fleming, King & Juda, 2007; Jaffe et al., 2002), we view citations as conduits for social attention. More importantly, we show how a guru’s social attention pool mediates between the advantage of collaborating with a guru and the likelihood that the focal designer will emerge as one. We thus provide a causal explanation for the observed advantages of guru collaboration. The findings reported in this study point to an important yet neglected issue in the literature on innovation through collaboration: the benefits of collaboration are a result not only of knowledge transfer effects but also of the attention sharing that stems from a collaborator’s social prominence. The innovation literature may well have overemphasized the importance of knowledge transfer at the expense of these social effects. In short, our study highlights the importance of examining knowledge effects and social effects when evaluating interpersonal collaborations.

Our focus on the phenomenon of guru emergence raises intriguing questions that can spark future research. For instance, given that achieving guru status is both desirable and highly challenging, how can
that status be sustained? Also, what factors might accelerate a decline from guru-ness? These are some of the questions that future work can explore to advance our knowledge about the fascinating topic of guru-ness.

This study relies on archival data derived from design patents, and that approach imposes a number of limitations common to research using patent activity. The findings reported here are based on successful collaborations—in other words, those resulting in patents that are actually granted. However, designer–guru collaborations may sometimes fail. Yet this should not jeopardize our conclusions because the focus here is on how collaboration affects exceptional outcomes (i.e., becoming a guru). By evaluating the work of designers in terms of the USPTO’s presumably consistent standards, we ensure that our definition of a guru is consistent and hence that our comparisons (and conclusions) across time are justified.

In scanning 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, in their younger days, studied under the gurus of their era. Our paper is the first one that employs a temporally extensive patent data set to quantify the effects of collaborating with a guru and thus to identify the mechanisms that underlie the phenomenon of “gurus breeding gurus”. A unique aspect of this exploration is our finding that the importance of knowledge transfer in such collaborations should be considered while accounting also for the social effects of attention sharing. A firm can exploit these results to cultivate future gurus and thereby further its own design competitiveness—thus gaining enough leverage, perhaps, to influence the direction of entire industry segments.

REFERENCES


### Table 1. Taxonomy of Literature on Creative Performance and Collaboration

<table>
<thead>
<tr>
<th>Collaboration with non-gurus</th>
<th>Collaboration with gurus</th>
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<tr>
<td><strong>Average creative performance</strong></td>
<td><strong>Superior creative performance</strong></td>
</tr>
<tr>
<td>• Fleming, Mingo &amp; Chen (2007)</td>
<td>• Waldinger (2010)</td>
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<td>• Sosa (2011)</td>
<td>• Sosa (2011)</td>
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<td>• Tortoriello &amp; Krackhardt (2010)</td>
<td>• Tortoriello &amp; Krackhardt (2010)</td>
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### Table 2. Summary Statistics and Correlations

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<td>2. Direct ties to non-gurus (Ln)</td>
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### Table 3. Collaboration Patterns of Designers and Percentage of Gurus

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<tr>
<th>Collaboration pattern</th>
<th># of non-gurus</th>
<th># of gurus</th>
<th>Total</th>
<th>Percentage of gurus (/# of gurus/Total)</th>
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<tbody>
<tr>
<td>Collaborate with guru</td>
<td>17,508</td>
<td>5,429</td>
<td>22,937</td>
<td>23.67%</td>
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<tr>
<td>Collaborate with non-guru</td>
<td>90,191</td>
<td>5,681</td>
<td>95,872</td>
<td>5.93%</td>
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<tr>
<td>No collaboration</td>
<td>92,722</td>
<td>3,822</td>
<td>96,544</td>
<td>3.96%</td>
</tr>
<tr>
<td>Total</td>
<td>200,421</td>
<td>14,932</td>
<td>215,353</td>
<td>6.93%</td>
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### Table 4. Proportional Hazard Model for Likelihood of Guru Emergence

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<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
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<td>Direct ties (Ln)</td>
<td>0.329***</td>
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</tr>
<tr>
<td></td>
<td>(0.023)</td>
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<tr>
<td>Direct ties to gurus (Ln)</td>
<td>0.613***</td>
<td>1.141***</td>
<td>0.879***</td>
<td>0.624***</td>
<td>0.528***</td>
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<td>(0.039)</td>
<td>(0.042)</td>
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<td>(0.069)</td>
<td>(0.070)</td>
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<tr>
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<td>0.400***</td>
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<td>(0.022)</td>
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<td>(0.034)</td>
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<td>Non-guru's direct ties</td>
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<tr>
<td>Mobility</td>
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<td>0.274***</td>
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<td>Selectivity</td>
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Notes: n=174,790. Robust standard errors are reported in parentheses. All models control for cohort dummy variables. *p<0.05, ** p<0.01, *** p<0.001
Figure 1. Marginal Effect of Collaborators

Figure 2. Counterfactual Framework of Mediation
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