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Structural Microfoundations of Innovation: The Role of Relational Stars

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Conceptualizing new knowledge development as a process of search and recombination, we suggest that a focus on individual productivity alone presents an undersocialized view of human capital. Rather, we emphasize the importance of embedded relationships by individuals to effectively perform knowledge-generating activities. We rely on intraorganizational knowledge networks emerging through individual collaboration to identify actors who can positively influence their organization's knowledge outcomes. We study two types of such relational stars: integrators (outliers in centrality) and connectors (outliers in bridging behavior). We test our ideas using the patenting portfolios of 106 pharmaceutical firms from 1974 to 1998 predicting the effect of relational stars on their firm's quantity and quality of inventive output—proxies for the

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firm's capacity to develop more and better new knowledge stocks. We find that the presence of relational stars results in firm-level knowledge advantages not only through their own superior recombinant efforts, but also through their capacity to make others around them more effective at knowledge recombination. Relational stars are firm-specific, and their advantages are socially complex and causally ambiguous because they rely on a network of within-firm interactions. Relational stars, therefore, are prime candidates to be a source of sustainable firm-level knowledge advantage.

Keywords: *microfoundations; strategic human capital; knowledge and innovation management; social networks*

Since Schumpeter (1942) we have known that innovation is a vehicle of economic growth and a potential source of firm-level performance heterogeneity. Scholars have convincingly argued that innovative organizations are those with superior routines (Nelson & Winter, 1982), capabilities (Kogut & Zander, 1992), competences (Henderson & Cockburn, 1994), or dynamic capabilities (Teece, Pisano, & Shuen, 1997). The simple observation that knowledge is the key raw material for innovation (Nonaka, 1994) combined with the recognition of individual actions and interactions as an appropriate locus of knowledge (Felin & Hesterly, 2007), however, directed attention to the role of individuals as the microfoundations of the firm-level capabilities (Felin & Foss, 2005). Indeed, research indicates that the so-called star knowledge workers or star scientists can provide organizations with an innovation advantage mainly because of their own superior capacity to generate ideas and knowledge (Groysberg, Lee, & Nanda, 2008; Lacetera, Cockburn, & Henderson, 2004; Rothaermel & Hess, 2007; Zucker, Darby, & Brewer, 1998).

Although a focus on "productivity stars" is certainly an important first step in uncovering microfoundations of firm-level performance heterogeneity, it nonetheless presents a somewhat undersocialized account of human capital. Few productivity stars are "lone wolfs" (Hess & Rothaermel, 2012); rather they are embedded in social and knowledge networks deep within firms (Groysberg et al., 2008). Here, instead of looking at either productivity stars or network stars, we combine the two individual-level properties and explain and show how individuals who are both strong knowledge producers and great collaborators enhance their firm's innovative output. We refer to these individuals as "relational stars." Traditional productivity stars are outliers in their ability to generate new knowledge or ideas. Relational stars are outliers in their capacity to not only generate knowledge but also form, maintain, and effectively manage knowledge relationships within firms. They can be individuals who have large, dense, or far-reaching networks of collaborators. They can be individuals whose collaborative behavior allows them to operate as the linking pins among internally distant and otherwise unconnected clusters of knowledge. We argue that relational stars can rely on their collaborative behavior to not only identify more opportunities for knowledge recombination but also select the most promising ones, leading to knowledge of higher quality. We further submit that relational stars can make actors around them more productive and increase the effectiveness of firm-wide knowledge recombinant search through opening up hidden avenues for further recombination. Overall, with the introduction of relational stars we are trying to hone in more closely on the locus of intrafirm knowledge creation and draw a

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tighter theoretical connection between micro-level behavior and firm-level knowledge outcomes (Felin & Foss, 2005).

We submit that the introduction of relational stars represents a theoretical contribution to achieve a more fine-grained understanding of the role of human capital as a potential source of knowledge-based competitive advantage. Evidence suggests that knowledge development is a communal team-based endeavor (Wuchty, Jones, & Uzzi, 2007). New knowledge comes from effective knowledge sharing (Hansen, 1999), search (Gavetti & Levinthal, 2000; Katila & Ahuja, 2002), transfer (Tsai & Ghoshal, 1998), recombination (Galunic & Rodan, 1998), reconfiguration (Henderson & Cockburn, 1994), diffusion (Zollo & Winter, 2002), and renewal (O'Reilly & Tushman, 2007). In other words, new knowledge development requires the implementation of inherently socially intensive processes. As a result, the individuals involved in knowledge creation and commercialization must also possess social and collaborative skills. The concept of relational stars helps us to better understand the microstructure of organizational capabilities that can result in improved firm-level innovative performance. We also conjecture that relational stars might have a relatively stronger impact on firm-level heterogeneity than simple productivity stars because as a socially complex resource deeply embedded within intrafirm knowledge networks, they attract much less attention and thus are less likely to extract their true resource value (Barney, 1991; Dierickx & Cool, 1989). As a result, we attempt to shed some light on a set of relatively neglected human capital resources with the strong potential to provide their firms with knowledge-based competitive advantage.

Finally, the concept of relational stars contributes to research on the interaction of human capital, social capital, and knowledge networks. Existing research shows that an individual's position in the internal network may affect that individual's involvement in innovation (Obstfeld, 2005), creativity (Fleming, Mingo, & Chen, 2007), and performance (Gargiulo, Ertug, & Galunic, 2009). In addition, the structure of the knowledge network may affect the overall network's knowledge performance (Brown & Eisenhardt, 1997; Reagans & McEvily, 2003; Reagans & Zuckerman, 2001). Much less is known, however, with respect to the effect of individual nodes in certain positions on the overall firm network's performance. A recent review of network research concludes that this micro-to-macro gap remains (Kilduff & Brass, 2010). We make an effort to illuminate and document the theoretical mechanisms through which the presence of an individual network position (that is, a certain pattern of individual collaborative behavior) may affect not only that individual's performance but also the performance of the firm as a whole. We explain why relational stars are a valuable resource for firm-level innovation. In particular, we show how the development of internal social capital by certain individuals results in superior human capital, which in turn can lay the basis for a competitive advantage. To document this empirically, we employ a longitudinal design and track over 500,000 knowledge workers listed as inventors in patents and employed by 106 companies in the global pharmaceutical industry.

Theory and Hypotheses

Organizational research on the antecedents of knowledge generation has long been dominated by the notion of routines (Nelson & Winter, 1982). The knowledge-based conceptualization of the firm as a social community guided by higher-order principles that are irreducible to individuals spurred significant research efforts linking capabilities directly to

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organizational knowledge outcomes (Henderson & Cockburn, 1994; Kogut & Zander, 1992; Teece et al., 1997; Zollo & Winter, 2002). Research in the knowledge-based paradigm, however, emphasized the importance of accounting for individuals to understand the formation of such organizational capabilities in a more fine-grained manner (Conner & Prahalad, 1996; Grant, 1996; Nonaka, 1994). Linking capabilities with outcomes without considering individuals as their microfoundations opens the door for alternative explanations (Abell, Felin, & Foss, 2008). Theoretical support of individuals as a more appropriate locus of knowledge channeled some research toward the role of human capital in driving organizational innovation (Felin & Hesterly, 2007). Evidence suggests that firms enjoy several innovation-related benefits when they employ (even a few) highly productive individuals with the capacity to generate scientific knowledge. The so-called star scientists are instrumental for knowledge sensing (Lacetera et al., 2004), renewal (Zucker & Darby, 1997), knowledge capture (Zucker, Darby, & Armstrong, 2002), and adaptation to radical discontinuities (Rothaermel & Hess, 2007).

A sole focus on star performers and their superior productivity not only advances an impoverished and undersocialized view of human behavior, but also may even be misleading in our quest for the locus of knowledge within firms. First, we neglect to take into consideration the fact that individual creativity has an apparent social side (Perry-Smith & Shalley, 2003) and thus risk overemphasizing the role of the individual while underemphasizing the role of the team and ignoring the systemic aspects that affect firm performance (Pfeffer, 2001). Early research on the emergence of industrial R&D suggested that an advantage of the company research laboratory was that "it could take several [people], each lacking the necessary qualifications for successful independent research, and weld them into a productive team in which each member compensated for the others' shortcomings" (Beer, 1959: 71). Second, organizations have an advantage over individuals because they can internally develop intellectual capital based on social interactions among their members (Nahapiet & Ghoshal, 1998), interactions that generate important knowledge-related spillovers as knowledge workers not only complement each other but also actively help one another (Oettl, 2012). Firms can internalize such positive externalities and appropriate the knowledge advantages that they generate. Finally, we may overlook that highly productive individuals are by definition in limited supply, face increased demand in the developing war for talent, and have skills that are often not firm specific. Accordingly, they are visible to the market and are likely to be hired away as they can be easily identified by rival firms (Gardner, 2005; Peteraf, 1993). Alternatively, they may appropriate all or most of the value that they generate or threaten to leave the organization and transfer their knowledge to competitors (Almeida & Kogut, 1999).

To further understand the role of human-capital-based knowledge advantage, therefore, we suggest going beyond simply individual productivity to a set of individual-level social and collaborative skills that have not been considered sufficiently and in combination with human capital in their potential effect on firm-level outcomes. The importance of relational skills by knowledge workers within firms is especially critical to continued innovation, because innovation is conceptualized as a socially intensive process of knowledge recombination and knowledge transformation (Nahapiet & Ghoshal, 1998). Individuals innovate by searching for potential knowledge recombinations between familiar and new components (Fleming, 2001). Socialization as well as intraorganizational persuasion and conflict are

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important components of successful search outcomes (Fleming, 2002; Gavetti & Levinthal, 2000). Firms need to integrate disparate pieces of knowledge (Henderson & Cockburn, 1994) and dynamically reconfigure their existing knowledge stocks as markets evolve (Galunic & Eisenhardt, 2001). To create novel recombinations, knowledge needs to be accumulated and reused to result in innovation (Murray & O'Mahony, 2007). To effectively perform these activities, individuals need to possess relational capacities to collaborate and form extensive intrafirm knowledge networks. In addition, an empirical link between these relational skills and firm-level knowledge development has significant implications for the sustainability of such human-capital-based knowledge advantage: These skills exist across different levels—the individual and the firm—and therefore make firm specificity, social complexity, and causal ambiguity of advantage even more promising as potential sources of sustainable advantage (Coff & Kryscynski, 2011).

It is important to note that these individual-level relational skills within broader knowledge networks have been studied in the social capital and networks literature. There is research about the effect of an individual's network position on a host of meaningful individual-level outcomes (Brass, 1984; Cross & Cummings, 2004; Ibarra, 1993; Morrison, 2002), as well as research supporting the effect of the network's overall structure on network-level outcomes (Argyres & Silverman, 2004; Lazer & Friedman, 2007; Tsai, 2002; Yayavaram & Ahuja, 2008). Although there is some evidence that actors in certain positions affect organizational outcomes (Nerkar & Paruchuri, 2005), research on the role of individuals in these networks as drivers of firm-level outcomes remains scarce. Authors of network reviews echo this statement by calling for more research addressing cross-level network phenomena (Brass, Galaskiewicz, Greve, & Tsai, 2004; Ibarra, Kilduff, & Tsai, 2005). This is because we have limited theory and evidence linking individual positions in individual-level networks with firm-level knowledge outcomes. Existing theory and evidence explore the role of individuals that are strong in either human or social capital. Taken together, we have a limited level of understanding on how the development of individual-level social capital and human capital interact to result in firm-level knowledge advantages.

Relational Stars

We make an effort to address this gap by introducing the concept of relational stars. Relational stars are actors with extreme patterns of collaborative behavior and superior individual productivity. Through their own productivity and collaborations combined with the productivity and collaborative behavior of their alters, relational stars end up occupying positions in their firms' internal knowledge network that are consequential for the performance of the network as a whole.

Herein, we link relational stars with organizational outcomes. The behavioral pattern of a relational star has two components: what the individual can do with the network position that results from his/her collaborative behavior and prior productivity performance (function) and what the individual represents (role), also derived from the position. Clearly, the two are closely intertwined. We focus on explaining why the presence of relational stars translates into firm-level innovation outcomes. As a result, we address the previously identified gaps by showing that collaborative skills in combination with individual productivity matter and

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that individuals with extreme collaborative behavior affect not only their own performance but also the performance of the firm-level network as a whole.

Importantly, if relational stars are defined relative to their peers in an organization's internal network, then every organization would have its own share of these actors. Instead, we define relational stars relative to their counterparts in every competing organization's network. This approach mirrors research on "star scientists" where stars are the actors at the top of the productivity distribution of all scientists across firms. Hence, we attempt to document the role of relational stars as the origins of firm-level innovative performance. This in turn allows us to link micro-level factors to macro-level outcomes. We emphasize that relational stars are actors with extraordinary patterns of collaborative behavior with concurrent superior individual performance. We look for outliers in the collaboration-related distributions across all firms. We further extend this idea to add an additional dimension of being outliers in the productivity distribution across all firms. We conceptualize relational stars as those who are at the top of those distributions.

To choose the most relevant collaboration-related dimensions, we follow prior research on networks, which suggests that centrality and bridging behavior are the two most important characteristics associated with an individual's position in a social network. Subsequently, we develop hypotheses for two broad types of relational stars: integrators and connectors. We make the distinction to highlight the different mechanisms through which the two types of relational stars affect firm-level knowledge outcomes. Rather than distinguishing between differential effects on firm-level outcomes, we suggest that both types of relational stars may have a similar organizational-level impact, yet the underlying theoretical mechanisms are different. Prior network research supports the idea that centrality and brokerage result in qualitatively different benefits, and that is what we are emphasizing with the distinction. We depart from prior work, however, because rather than identifying and describing generic network positions, we highlight the role relational stars have on firm-level heterogeneity. This implies that the key actors in our study—integrators and connectors—need to satisfy additional requirements beyond centrality and brokerage to have firm-level performance implications. In addition, we further extend prior work by taking the two broad types of relational stars and adding an extra requirement to come up with "true" relational stars. Star integrators and star connectors are those among our set of relational stars that are also at the very top of the individual productivity distribution. All types of relational stars possess strong combination of both human and social capital, that is, a strong individual-level productivity performance combined with a highly consequential network position. The only difference is that "true" relational stars are also at the very top of the productivity distribution instead of simply being superior to the average knowledge producer.

Integrators

Integrators are the actors who have an extraordinarily large, extensive, and dense network of intrafirm collaborators. They are the glue that holds together dense interindividual knowledge cocreation clusters. Generally, integrators occupy a highly central position in their firm's internal network. The positive effect of such a central position on individual level outcomes has been documented in a number of studies. Centrality is associated with an individual's promotions (Brass, 1984), exercise of power (Ibarra, 1993), supervisor ratings

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(Mehra, Kilduff, & Brass, 2001), socialization (Morrison, 2002), innovative performance (Cross & Cummings, 2004), involvement in innovation (Obstfeld, 2005), and performance bonus (Gargiulo et al., 2009). Much less is known, however, with respect to the role of such individuals on the performance of the network as a whole. In an attempt to close this gap, we link the presence of integrators in an organization's collaborative network with network-level knowledge outcomes. We define integrators as universal outliers. In particular, integrators are individuals whose collaborative behavior involves a number and density or reach of alters that is large not relative to their peers in their organization's network but relative to all individuals in competing organizations. We argue that organizations employing such collaborative outliers enjoy an advantage in their innovation output. We choose the term "integrators" to highlight their main function: knowledge integration from many sources. Integrators are not just central in their firm's network; their number and density or reach of collaborative ties put them at the top of the distribution when compared with the population of individuals from competing organizations.

The main mechanism through which integrators affect network-level outcomes is their capacity to execute a highly effective micro-evolutionary process of knowledge recombination. First, integrators rely on significant variation: Through the knowledge inflows embedded in their many and frequently far-reaching collaborative ties, integrators observe a large number of alters, understand who knows what (Borgatti & Cross, 2003), and source knowledge from many actors. Integrators, therefore, have the capacity to identify more potential knowledge recombinations. Collaborative outliers (like the integrators here) have a disproportionate advantage (compared to simply actors with many, but fewer, ties) in this respect because every additional tie has an exponential effect on the number of potential recombinations. Such potential recombinations can be performed by the integrators themselves, by their existing alters, or by new network actors that can be added or reinstituted in the future. Such recombinations create a virtuous cycle and open up avenues for further recombinations by existing or new alters. This process of significant variation uniquely equips integrators to affect the overall *quantity* of their firm's innovation output. In addition, integrators rely on a process of stronger selection: They have the capacity to familiarize themselves with many potential recombinations and experiment with them to identify the most promising ones for realization. Stronger selection occurs either because informed integrators themselves make a better choice or because they rely on a large network of alters to make a more effective selection. In any case, this process makes them valuable for the overall *quality* of their firm's innovation output. This view is consistent with evidence that knowledge of central actors is more likely to be found in their firm's future technological capabilities (Nerkar & Paruchuri, 2005).

The presence of integrators in a firm's network, moreover, makes others around them more effective at knowledge generation. Integrators use the knowledge outflows embedded in their ties to effectuate diffusion of a constantly updating knowledge base to initiate further cycles of knowledge refinement. Evidence suggests that integrators should be able to diffuse knowledge easier than others as they exert significant influence on their peers (Brass, 1984). That means that their alters or other possible network participants are building on a knowledge base that includes frequent and more effective recombinations. This in turn initiates a virtuous upward cycle of further knowledge recombination and knowledge creation. Furthermore, the presence of integrators creates some of the conditions that have been shown

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to be favorable when it comes to knowledge development. They operate as the glue that increases the network's density and makes it promising for knowledge sharing. Centralized R&D structures have been shown to generate more impactful innovations (Argyres & Silverman, 2004), and cohesive structures positively affect individual motivations to share (Reagans & McEvily, 2003) or transfer knowledge (Reagans, Zuckerman, & McEvily, 2004). Taken together, integrators have the capacity to integrate knowledge locally for both higher frequency and higher quality of recombinations, diffuse the updated knowledge base throughout the organization, and create the conditions for further high-quality innovation to occur.

> *Hypothesis 1:* A firm's innovation output is a positive function of the number of integrators in its internal collaborative network.

Connectors

Connectors are actors who collaborate with previously unconnected alters and recombine knowledge coming from distant clusters of knowledge. Consequently, their network position is one that spans internal structural holes and allows them access to diverse parts of their firm's knowledge network. Prior research suggests the notion that brokers—individuals who span structural holes in a knowledge network—are more likely to come up with better ideas (Burt, 2004), are more creative (Fleming et al., 2007), and can adapt better to changes in the task environment (Gargiulo & Benassi, 2000). We extend current understanding on the role of brokers by introducing the concept of connectors that includes a combination of brokering and access to distant parts of the knowledge network. This additional requirement is not trivial as it allows us to develop arguments for the positive effect of connectors on the performance of the network as a whole and thus highlight the role of connectors in explaining firm-level heterogeneity. While not necessarily productive or highly collaborative, connectors operate as linking pins among otherwise unconnected and distant knowledge stocks. They are not only rich in structural holes; their spanning of such holes also allows them to access a large share of the broader collaborative network in which they are embedded. In a sense, they are efficient knowledge brokers; their collaborative behavior bridges knowledge silos within their firm's network. As with integrators, we also define connectors in relation to the population of individuals in competing firms. In particular, connectors are individuals who span the highest number of structural holes in a network and access the highest share of their network compared to brokers in other competing organizations' networks.

The main mechanism through which connectors affect network-level outcomes is their capacity to execute a process of knowledge recombination based on more radical variation. Connectors use their ties' knowledge inflows to access diverse, distant, and previously unconnected sources of knowledge. They are more likely, therefore, to identify potentially novel and higher-quality knowledge recombinations. Potential recombinations can be performed by the connectors themselves, by their existing alters, or by new network actors that can be added or reinstituted in the future. Such recombinations create a virtuous cycle and open up avenues for further recombinations by existing or new alters, new alters that may be added to perform the radically new recombinations. Connectors have a capacity to collaborate across knowledge boundaries and access heterogeneous knowledge stocks, thus engaging in high-risk, high-return inventive trials. Uncovering links where none existed before

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allows them to further build on them to identify more and better possible recombinations and eventually positively affect both the *quantity* and *quality* of their firm's innovation output. The increase in quality is also driven by the fact that connectors have access to the evaluation of possible recombinations from actors coming from diverse knowledge standpoints.

The presence of connectors also makes actors around them better at knowledge generation. Through their outflows, connectors diffuse new knowledge to distant clusters of knowledge for further quality recombinations. Their alters can rely on recently uncovered links to build on them and generate more recombinations. Furthermore, these alters are not simply part of a dense local network of interactions but belong to a diverse set of knowledge clusters. Actors with diverse perspectives can simultaneously explore further knowledge recombinations of recently uncovered links. In addition, the presence of connectors in an organization's collaborative network creates some conditions that are favorable for higher-quality innovation. Connectors promote relaxed structures that facilitate improvisation (Brown & Eisenhardt, 1997), network heterogeneity that enables learning (Reagans & Zuckerman, 2001), and network range that supports knowledge transfer (Reagans & McEvily, 2003), and they also decrease the path length between any two actors in the network, thus improving its overall performance (Cowan & Jonard, 2003).

Hypothesis 2: A firm's innovation output is a positive function of the number of connectors in its internal collaborative network.

Star Integrators and Connectors

It follows from the previous discussion that both integrators and connectors are generally actors who also exhibit superior productivity when compared to the average actor inside their firm's internal collaborative network. Coleman (1988) was among the first to identify the connection between social and human capital. It is quite reasonable to believe that individuals with high levels of human capital constantly attract potential collaborators and as a result also increase their social capital. On the other hand, it is also reasonable to believe that individuals with high levels of social capital enjoy such informational advantages that make them more likely to further increase their human capital. We noted earlier that our relational stars occupy certain network positions in their firms' knowledge networks that make them highly consequential for the knowledge performance of their firm as a whole. However, the origin of their network position is probably a combination of their human capital, certain individual-level motivations, organizational structure and incentives, and so on. Relational stars emerged in their positions through a dynamic interplay between their human and social capital. We also noted that more likely than not, simple integrators and connectors are not only network stars but should also be superior to the average actor in terms of individual productivity as a result of or as a driver of their network position. Here, we take this idea one step further and explicitly hypothesize an effect coming from "true" relational stars, that is, integrators or connectors who are at the same time at the very top of the productivity distribution. They are, in other words, also productivity stars. Recent work by Oettl (2012) suggests that productivity stars can be "lone wolves" or "all-stars" (indicating individuals who produce for themselves but also help others through advice). He found that those "all-stars" have the highest positive effect on the performance of their alters. Building on this work and combining our earlier points about the importance of relational stars on their firm's overall

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innovation output with existing theory and evidence about the importance of productivity stars, we argue that the positive effect of relational stars will be even stronger for the relational stars who also happen to be productivity stars. Therefore, we suggest that individuals with a combination of strong human capital and expansive social capital will have the strongest positive effect on their firm's innovative output.

Hypothesis 3a: The positive effect of integrators on firm-level innovation output is stronger if the integrator is also a star inventor.

Hypothesis 3b: The positive effect of connectors on firm-level innovation output is stronger if the connector is also a star inventor.

Method

It is important to note here that relational stars are conceptually distinct from simple firm-level average phenomena. First, our typology of relational stars captures outliers of two distributions. The critical difference is between looking at the extremes of a distribution (as in our case at the individual level) and looking at the mean (as it would be if one looks at firm-level averages). For example, one can observe a firm-wide network that on average is highly centralized and dense without having a single integrator (defined as an outlier drawn from the population of competing firms). Similarly, one can observe a firm-wide knowledge network that is on average highly fragmented without identifying a single connector (again, relative to the population). Interestingly, identifying the outliers identified herein (integrators and connectors) is important above and beyond average firm-level phenomena. That is because every additional tie at the individual level increases exponentially the potential for relational stars to facilitate and execute effectively the processes of recombination, diffusion, and so on, through which they have their main effects on firm-level knowledge outcomes. Admittedly, the number of integrators and connectors is affected by the overall size of the network. The most important challenge when it comes to documenting individual- to firm-level effects is to control for firm-level variables that affect both individuals and outcomes. To do that, we rely on a large, multifirm, longitudinal empirical design with many controls to carefully take into account many aspects of network size and other firm-level actions that have been shown to affect innovation output at the firm level.

Empirical Design

To empirically test the developed hypotheses, we followed a longitudinal research design in the global pharmaceutical industry. Firms in this industry are under constant pressure to innovate. In addition, they had to face the emergence of biotechnology as a new paradigm in product development, a discontinuity that increased existing pressures to keep innovating to survive. To respond, pharmaceutical firms engaged in a wide array of alternative strategies to remain innovative; they took on alliances, acquisitions, and heavy investment in internal research and human capital to build or maintain innovative capabilities (Rothaermel & Hess, 2007). The pharmaceutical industry provides an ideal setting for our attempt to explore the role of relational stars in driving innovation output above and beyond the mentioned innovation levers.

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The study is longitudinal in design; it covers the time period from 1974 to 2006. The sample drawn consists of 106 global pharmaceutical firms that were active in the production of human in vivo therapeutics. To control for firm entry by biotech companies, all companies in the sample are incumbent pharma firms that we founded prior to 1974, which demarcates the pivotal scientific breakthrough in recombinant DNA (Galambos & Sturchio, 1998). This sample is largely representative of the overall industry as it accounts for the vast majority of global sales of pharmaceutical products. We tracked these 106 firms forward until 1998 (and patent data until 2006). We control for horizontal mergers; when a merger occurred, we combined the data of the merging firms into one entity and continued tracking it forward. In addition, we created an indicator variable to capture a merged entity.

We constructed the key variables relying on patents granted to these firms by the U.S. Patent and Trademark Office (USPTO). It is important to emphasize here that we used inventor-level patent data to construct our independent variables and that we eventually aggregated these inventor-level data points up to the firm level to facilitate interfirm comparisons. The pharmaceutical industry is the industry that relies the most on patents when it comes to intellectual property protection compared to all other manufacturing industries (Cohen, Nelson, & Walsh, 2000). We used the National Bureau of Economic Research (NBER) patent data file (Hall, Jaffe, & Trajtenberg, 2001) to create a patent portfolio for each one of our firms from 1974 to 1998. We tracked all different names under which firms patent and collected patent data for their subsidiaries to make sure that we had each firm's complete patenting record. From the resulting patent portfolios, we kept information about dates of applications, citations received, claims made, inventors listed, and technology classes assigned. Most firms in our sample are dedicated pharmaceutical firms; however, there are also a few diversified companies that are also active in other industries. We explicitly control for this effect by including an indicator variable to capture nondiversified pharma companies. Since we explicitly control for the level of diversification (if any), we sampled on the resulting patent portfolio for each firm in the sample. Moreover, we relied on information from technology classes to keep only patents with a clear chemistry or biology component, because these are more likely to be related to the technologies underlying human therapeutics.

Dependent Variables

To proxy the *quantity* of a firm's innovation output, we used the annual count of patents granted to the sample firms. Although patents capture invention more accurately than innovation per se, we followed the convention in prior research that measured innovative output by a firm's patents (e.g., Ahuja, 2000; Henderson & Cockburn, 1994; Owen-Smith & Powell, 2004; Rothaermel & Hess, 2007). To proxy the *quality* of a firm's innovation output, we used the number of citations that a firm's patents in year *t* received in subsequent years until 2006. Note that although our firm sample period ends in 1998, we track firm patent citations until 2006. We relied on the application date for the patents because it is much closer to the actual time of invention than the granting date. Evidence suggests that the number of citations received by a patent is a significant predictor of its market value (Hall, Jaffe, & Trajtenberg, 2005) and has been used to measure the usefulness of innovations (Yayavaram & Ahuja, 2008). In addition, as a robustness check for the quality of a firm's innovation output, we

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used the number of claims made by a firm's patents. Claims arguably represent a measure of a patent's technical quality and have been used in prior research to measure the quality of a firm's innovation activities (Singh, 2008).[1]

Intrafirm Collaborative Networks and Independent Variables

To identify relational stars and create the key independent variables for this study, we developed intrafirm coinventing networks for each firm from 1974 to 1998. These are fine-grained, individual-level knowledge networks embedded within each firm. We relied on the NBER database inventor file and assigned a unique ID to each individual inventor based on a combination of last, first, and middle names. When there was still a conflict, we expanded our matching criteria to include city and state of residence for each inventor. The resulting data set was a file for each firm with unique inventors IDs assigned to each patent from 1974 to 1998. As a next step, we used UCINET 6 to develop intrafirm coinventing networks. Network nodes are individual inventors and ties are copatenting events among them. Our main argument is that these ties involve knowledge flows, and thus we proceeded by characterizing knowledge through a tie that is older than 5 years as obsolete. Therefore, we developed the knowledge networks using a 5-year rolling window and assigned the resulting values to the last year of each time window (e.g., 1992-1996 values to 1996, 1993-1997 values to 1997, etc.). We analyzed our network and kept a wide array of detailed ego network metrics to define relational stars. In a final step, we constructed the key independent variables for this study—integrators and connectors.

Integrators. To achieve a close match between our theoretical arguments and empirical estimation, integrators had to be inventors who are outliers in terms of their collaborative behavior (number of ties) combined with an ego network characterized by high density or high reach. That is, for integrators to have the hypothesized effects we needed inventors with either a large dense network of collaborators or a large network of collaborators which reaches a large part of the overall network. This approach mirrors the two faces of centrality: Individuals can be central because they possess power. These actors possess many alters, who in turn are connected to many others. Alternatively, individuals can be central because their many ties allow them to reach a wide part of the overall network. Therefore, to empirically capture integrators we followed two related approaches. First, we identified inventors with direct collaborative ties that are at the top decile of the distribution of ties of all inventors of all firms during the same 5-year window. Then, among the resulting set of actors, we proxied integrators as inventors at the top half of the density distribution with more than one patent during the time window (to exclude one-time inventors). The indicator variable *integrator–power* captures integrators using this first approach. In the second approach, we relied on the distribution of the "two-step reach" metric from UCINET, which measures the percentage of the overall network that an actor accesses with his or her direct and indirect ties. The indicator variable *integrator–reach* captures actors who are at the top of the two-step reach distribution of all inventors of all firms during the same 5-year window.[2]

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Connectors. We emphasized that connectors are not only knowledge brokers in terms of spanning many structural holes, but also individuals who connect distant clusters of knowledge and have access to a large share of their firm's collaborative network. Connectors need both brokerage and reach to distant clusters to have the hypothesized firm-level effects through novel variation, link among diverse clusters, and diffusion to distant knowledge silos. Therefore, to capture connectors we relied on a combination of two network metrics. First, we selected inventors with an ego network density that is at the bottom quartile of the density distribution among the population of inventors from the sample firms during the same 5-year time window. A low density among one's alters means that one is connected to actors who are not connected to each other; therefore, one spans many structural holes. Hence, we first sampled on inventors who span structural holes. Among them, the indicator variable *connector* captures inventors whose two-step reach was at the top half of the reach distribution. Therefore, among the inventors who span structural holes, connectors are those whose ties allowed them to reach a sizeable share of the firm's internal collaborative network, thus excluding inventors who bridge structural holes but do so at the periphery of the network.[3]

Star integrators and connectors. These two types of "true" relational stars are fairly straightforward. Star integrators are the inventors who are at the same time "integrators–power" or "integrators–reach" and "stars." Star connectors are the inventors who are at the same time both "connectors" and "stars." "Stars" are the inventors with patents that are three standard deviations above the mean number of patents of every other inventor in the same 5-year time window.

Using these indicator variables at the inventor level, we developed independent variables at the firm level using counts of *integrators–power, integrators–reach, connectors, star integrators–power, star integrators–reach*, and *star connectors* that each firm possesses in each year from 1974 to 1998 (again, counts from the time window 1974-1978 go to 1978, counts from 1975-1979 go to 1979, etc.). It is important to note here that we also empirically confirmed the focus on these three types of individuals. We ran a factor analysis at the individual level of analysis with the ego network metrics as the variables of interest. This analysis resulted in three main factors explaining the majority of variance: first, a factor that groups together low density and high brokering behavior corresponding to *connectors*; second, a factor that includes a large number of ties with high centrality corresponding to *integrators–power*; third, a factor that includes a large number of ties coupled with large two-step reach corresponding to *integrators–reach*.

Control Variables

We included a series of control variables to rule out a host of alternative explanations. First, we included variables to control for firm-level strategy for new knowledge development, exploration of and performance in the new domain of biotechnology, some firm-level characteristics, and so on. First, we included the *number of exploration* and *exploitation alliances* in our models to control for the effect of alliance activity (intended for either exploration or exploitation) on innovation output. We collected data on every firm's alliance portfolio

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from the BioScan directory and the ReCap database. Following prior research, we coded grant, research, and R&D alliances as *exploration alliances* because the focus of these alliances is the enhancement of upstream research and basic science capabilities. We also included the *number of biotech-related acquisitions* in our model to control for the effect of rapid talent infusion on inventive output. We relied on the SDC Platinum database for data on acquisitions. In addition, we controlled for the number of *biotech patents* and *the ratio of biotech to all patents* to capture the performance of firms in the emerging biotechnology paradigm and the relative focus of the firm on biotech. To identify biotech patents, we relied on the definition of a biotech patent provided by the Patent Technology Monitoring Division of the USPTO. When predicting quality of inventive output, we also controlled for the quantity of it by including firm-level patent counts as a right-hand-side variable. Furthermore, our longitudinal design allowed us to control for temporal effects by including year indicators. Finally, we used controls for merged entities (*merged*) to capture horizontal mergers, for national origin (*US* and *EU*), and for the main industry of each firm's activities because some firms are diversified outside human therapeutics (*Pharma*).

More important, we explicitly control for star inventors, network size, firm size, collaborative patterns, and network structure. First, we control for the number of star inventors (*stars*). We defined stars based on their above average productivity. At the inventor level, a star is an indicator variable capturing inventors with patents that are three standard deviations above the mean number of patents of every other inventor in the same 5-year time window. At the firm level, *stars* is a variable counting the number of star inventors for every 5-year window. We controlled for *network size* and *5-year inventors*, arguably two of the main drivers of the development of integrators and connectors, since the larger the network the greater the opportunities for individuals to establish connections and become integrators or connectors. Hence, by controlling for network size we ran conservative tests for our hypotheses. This is because we were able to show that integrators and connectors affect innovation output beyond any effect of the overall network size. To proxy for firm size and develop a fine-grained measure of research investment, we included *annual inventors*, which is a variable capturing the number of inventors listed in a firm's patents on an annual basis. Finally, we controlled for *average coinventors* on a per-year basis to proxy for changing collaborative patterns and for *network density* to proxy for an important characteristic of the firm's underlying network structure.

Estimation Procedures

Our main dependent variables (firm-level patent counts and citations—claims as robustness check) are all nonnegative overdispersed count variables. We used the negative binomial estimation method with fixed-effects specification to conduct a within-firm analysis and control for any remaining unobserved heterogeneity (Greene, 2003).[4] We estimated each model with bootstrapped standard errors. In addition, we used a number of alternative regression procedures to assess the robustness of our estimation. First, we estimated the models using fixed-effects Poisson with robust standard errors. Second, we estimated the models using fixed-effects least squares with robust standard errors predicting the logarithm of our count dependent variables. The main findings were the same; we report differences, if any, in the results section. Overall, the longitudinal nature of the empirical design, the definition

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of independent variables using 5-year rolling windows, and a rich set of control variables suggest that we contained any remaining endogeneity concerns as much as possible (Hamilton & Nickerson, 2003).

Results

Table 1 depicts descriptive statistics and bivariate correlations. Correlations among independent variables are below the recommended ceiling of .70. To further evaluate the possibility of collinearity, we estimated the variance inflation factors (VIFs) for each coefficient, with the maximum estimated VIF being 4.8, which is well below the recommended threshold of 10 (Cohen, Cohen, West, & Aiken, 2003). We observe, however, that correlations among types of relational stars, although below the recommended threshold, are still slightly elevated. This is the result of aggregation of roles at the firm level and does not reflect similarities at the individual level. To support this claim, we submit the correlations at the individual level depicted in Table 2, which shows that for the 550,000 individual-level observations in the sample, correlations among independent variables are low. A second observation that is worth noting from the bivariate correlations is the role of network size as a significant driver of relational stars. Hence, we are confident that by including it as a control variable we are able to account for an important firm-level driver of the key independent variables. This allows us to establish the importance of relational stars above and beyond any effect stemming from firm size or network size.

In Table 3, we provide a description of the various individual roles, and in Table 4 we provide descriptive statistics and more details about the different types of relational stars and descriptive statistics about the "average inventor" in our sample for comparison purposes. There are two important observations from Table 4: First, unique inventors remain in the same role for 3 to 4 years on average. Since our study covers more than three decades these data suggest that we are indeed looking at meaningful outliers; individuals do not stay long in their role, and they do so only for consecutive years. This implies significant variance and change in our data, and a relatively low level of inertia in a firm's knowledge network. Second, we observe significant and theoretically expected differences in the network metrics associated with the different roles. Integrators have ego networks of much higher density and reach than the ones of connectors. The two types of integrators exhibit similar network size and density, but differ significantly in terms of their reach. Connectors are, in fact, bringing different components together, especially when compared to integrators. Indeed, connectors bridge structural holes (if one looks at the average density or nbroker metric), while connecting distant and otherwise relatively unconnected knowledge clusters (according to the average number of components shown in the table). Connectors are also the most productive among our individual roles. All of the relational stars have much lower productivity, however, when compared to productivity stars. They are, nonetheless, much more productive than the "average" inventor, thus confirming the argument that even "regular" relational stars are adequately productive. This evidence supports our theoretical conjecture that if relational stars do drive innovative performance, they do so because of their collaborative behavior and not necessarily because of their productivity. Evidence about our "true" relational stars shows a similar pattern in terms of network metrics that we identified with the "regular" relational stars. However, "true" relational stars are much more productive than every other

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Table 1
Descriptive Statistics and Bivariate Correlation Matrix

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 Patent counts	46.73	67.70																							
2 Patent citations	323.26	476.90	.88																						
3 Patent claims	523.10	767.36	.94	.89																					
4 Firm merged	0.12	0.33	.18	.14	.15																				
5 European firm	0.30	0.46	.18	.06	.13	.08																			
6 U.S. firm	0.34	0.47	.17	.31	.23	.16	–.47																		
7 Pharma firm	0.46	0.50	–.24	–.23	–.24	.01	.03	–.06																	
8 Exploration alliances	0.72	1.62	.23	.17	.21	.28	.04	.12	.02																
9 Exploitation alliances	0.34	1.00	.10	.08	.07	.16	–.01	.09	.10	.52															
10 Acquisitions	0.25	1.04	.16	.13	.14	.30	.03	.12	.08	.38	.17														
11 Biotech patents	18.30	26.66	.68	.58	.63	.36	.13	.18	.04	.43	.28	.35													
12 Biotech focus	0.52	0.62	–.15	–.15	–.15	.12	–.01	–.07	.27	.14	.11	.14	.20												
13 Network size	481.89	831.57	.71	.51	.57	.25	.19	–.06	–.17	.30	.15	.19	.58	–.02											
14 Network density	0.01	0.07	–.08	–.08	–.08	–.04	–.01	–.07	.05	.00	.02	–.01	–.06	.04	–.03										
15 Average coinventors	2.98	6.66	–.08	–.10	–.09	–.04	–.05	–.19	–.02	–.02	–.01	–.02	–.05	.03	.10	.32									
16 5-year inventors	237.38	292.67	.87	.74	.79	.26	.18	.06	–.28	.28	.13	.19	.61	–.09	.89	–.08	–.02								
17 Annual inventors	82.64	109.86	.94	.80	.86	.22	.19	.06	–.24	.29	.14	.19	.68	–.12	.86	–.07	–.01	.94							
18 Productivity stars	4.26	11.01	.72	.51	.57	.22	.18	.03	–.12	.26	.14	.18	.60	–.03	.87	–.04	–.01	.76	.78						
19 Integrators–power	8.67	19.37	.42	.26	.28	.13	.11	–.14	–.03	.19	.11	.12	.42	.05	.81	.01	.21	.56	.58	.69					
20 Integrators–reach	9.31	23.93	–.13	–.16	–.14	–.05	–.05	–.16	.14	.00	.02	–.04	–.02	.17	.14	.10	.35	–.07	–.05	.04	.43				
21 Connectors	10.04	18.68	.56	.38	.40	.22	.13	.01	–.11	.27	.18	.17	.53	.01	.82	–.04	.02	.65	.68	.83	.65	.04			
22 Star integrators–power	0.49	2.06	.44	.27	.32	.21	.13	–.03	–.05	.23	.13	.14	.44	.02	.69	–.02	.03	.51	.54	.82	.68	.11	.66		
23 Star integrators–reach	0.68	2.26	.06	–.01	.02	.11	.03	–.01	.06	.08	.07	.04	.16	.12	.28	.02	.10	.10	.12	.36	.43	.58	.30	.48	
24 Star connectors	1.35	3.18	.56	.41	.43	.26	.07	.15	–.08	.27	.18	.22	.59	.01	.69	–.04	–.04	.57	.60	.84	.54	.00	.81	.64	.36

Note: $N = 2{,}442$ firm-year observations.

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Table 2
Descriptive Statistics—Correlation Matrix at the Individual Level

		M	*SD*	1	2	3	4	5	6
1	Productivity star	0.019	0.136						
2	Integrator–power	0.039	0.192	.06					
3	Integrator–reach	0.041	0.199	.08	.27				
4	Connector	0.045	0.206	.18	–.01	.10			
5	Star integrator–power	0.002	0.047	.34	.23	.04	.00		
6	Star integrator–reach	0.003	0.055	.40	.03	.26	.07	.18	
7	Star connector	0.006	0.077	.56	–.01	.05	.36	.03	.22

Note: N = 550,921 individual-level observations.

Table 3
Description of Individual Roles

	Above Average Patent Productivity	Star Inventor (3 *SD*s)
No specific network position	N/A	Star
High power—many ties with density	Integrator–power	Star integrator–power
High reach—many ties with reach	Integrator–reach	Star integrator–reach
High bridging—structural holes among components	Connector	Star connector

Table 4
Descriptive Statistics—Individual Roles—Mean Values

	Star	Integrator–Power	Integrator–Reach	Connector	Star Integrator–Power	Star Integrator–Reach	Star Connector	Avg Inventor
Observations	10,319	21,232	22,845	24,525	1,196	1,658	3,298	551,672
Ties	18.38	13.60	12.27	11.73	17.07	29.00	15.27	4.28
Ego network density	34.91	65.76	72.54	32.57	57.78	31.52	27.79	73.85
No. of components	1.92	1.14	1.19	2.10	1.09	1.67	2.25	1.12
Two-step reach	12.35	17.63	36.26	11.84	14.46	37.11	12.91	4.28
Nbroker	0.32	0.17	0.14	0.34	0.21	0.34	0.36	0.08
No. of patents	22.84	5.70	5.13	8.25	20.22	24.03	21.38	2.65
Unique inventors	2,241	6,012	5,203	6,537	478	446	1,075	82,012
Average years in role	4.60	3.53	4.39	3.75	2.50	3.72	3.07	N/A
Percentage consecutive years	96.50	91.11	94.71	90.03	97.28	95.88	92.36	N/A

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individual role, and they are, as expected, much fewer in terms of their number of different inventors that are "true" relational stars.

Tables 5 and 6 depict the regression results predicting patent counts (quantity dimension of DV) and patent citations (quality dimension of DV). We follow a similar structure in the presentation of results in both tables. Model 1 includes control variables only and presents a baseline estimation. Model 2 includes the "regular" relational stars. In Model 3, we add the interactions among relational stars to control for any interaction effects. Model 4 includes the "true" instead of the "regular" relational stars, and Model 5 similarly includes their interactions. The results presented across the different estimations and models show a consistent pattern, supporting our theoretical arguments. In detail, integrators–power are positively and significantly associated with firm-level patent counts ($p < .05$, Model 2 and $p < .001$, Model 4 in Table 5) and patent citations ($p < .01$, Models 2 and 4 in Table 6). Integrators–reach are positively and significantly associated with firm-level patent counts ($p < .001$, Models 2 and 4 in Table 5) and patent citations ($p < .01$, Model 2 and $p < .1$, Model 4 in Table 6). Taken together, we find strong support for Hypothesis 1. Connectors are positively and significantly associated with firm-level patent counts ($p < .001$, Models 2 and 4 in Table 5) and patent citations ($p < .001$, Models 2 and 4 in Table 6). Taken together, we find strong support for Hypothesis 2. Star integrators–power are not significant drivers of patent counts or patent citations. Star integrators–reach are positively and significantly associated with firm-level patent counts ($p < .001$, Model 3 and $p < .01$, Model 5 in Table 5) and patent citations ($p < .001$, Models 3 and 5 in Table 6). We, therefore, find some support for Hypothesis 3a. Star connectors are positively and significantly associated with both patent counts ($p < .001$, Model 3 and $p < .05$, Model 5 in Table 5) and patent citations ($p < .01$, Model 3 and $p < .001$, Model 5 in Table 6). Taken together, we find strong support for Hypothesis 3b.

We also report some interesting results from our control variables. The size of the network and the size of the firm are both positively and significantly associated with inventive output for most of our models across estimation methods. Somewhat surprising, star inventors are generally negatively and significantly associated with the quantity and quality of inventive output. This is an interesting pattern of results about the role of stars on different dimensions of inventive output, a pattern that further validates the need to take into account relational stars. The results for star inventors should be interpreted with caution as we define them as star inventors (in terms of patenting) and not as star scientists (in terms of number of publications), as generally done in the existing literature. Interactions among the different types of relational stars are all not significant. It is evident that it is the direct effects coming from the different individual roles and not the interaction effects that matter. Although this is hard to argue based on a nonsignificant finding, this evidence provides some support for direct independent effects coming from the different types of relational stars.

Robustness Checks

We conducted a number of robustness checks, estimating the regression models with a different set of dependent variables emphasizing different dimensions and a rolling 5-year time window for key independent variables. The additional analyses are in line with the results reported below. The three types of relational stars are positively and significantly

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Table 5
Fixed-Effects Negative Binomial Regression Predicting Firm-Level Patent Counts (With Bootstrapped Errors)

Variable	Model 1			Model 2			Model 3			Model 4			Model 5		
Constant	2.270	***	(0.370)	2.310	***	(0.370)	2.306	***	(0.445)	2.360	***	(0.526)	2.328	***	(0.443)
Year effects	Incl.	***		Incl.	***		Incl.	***		Incl.	***		Incl.	***	
Merged	–0.084		(0.060)	–0.059		(0.070)	–0.081		(0.060)	–0.047		(0.057)	–0.075		(0.072)
EU	–1.036	*	(0.480)	–1.029	*	(0.420)	–1.048	*	(0.500)	–1.060	*	(0.529)	–1.029	†	(0.568)
US	–0.184		(0.440)	–0.207		(0.420)	–0.213		(0.604)	–0.225		(0.500)	–0.220		(0.582)
Pharma	–0.064		(0.280)	0.004		(0.260)	0.025		(0.273)	0.000		(0.286)	0.022		(0.270)
Exploration alliances	–0.013		(0.010)	–0.008		(0.010)	–0.009		(0.007)	–0.011		(0.010)	–0.009		(0.008)
Exploitation alliances	0.009		(0.010)	0.002		(0.010)	0.002		(0.008)	0.005		(0.009)	0.004		(0.009)
Acquisitions	–0.050	†	(0.030)	–0.039	*	(0.020)	–0.036		(0.024)	–0.037	*	(0.018)	–0.036	*	(0.018)
Biotech patents	0.004	**	(0.002)	0.004	*	(0.000)	0.004	*	(0.001)	0.003	†	(0.001)	0.004	*	(0.001)
Biotech focus	–0.016		(0.030)	–0.018		(0.040)	–0.015		(0.039)	–0.012		(0.043)	–0.014		(0.043)
Network size	0.000	*	(0.000)	0.000	**	(0.000)	0.000		(0.000)	0.000	**	(0.000)	0.000		(0.000)
Network density	0.131		(0.570)	0.301		(0.750)	0.128		(0.574)	0.299		(0.623)	0.118		(0.518)
Average coinventors	0.007		(0.010)	0.000		(0.010)	0.006		(0.011)	–0.001		(0.010)	0.006		(0.009)
5-year inventors	0.000		(0.001)	0.000		(0.000)	0.000		(0.000)	0.000		(0.000)	0.000		(0.000)
Annual inventors	0.005	***	(0.001)	0.005	***	(0.000)	0.005	***	(0.001)	0.005	***	(0.001)	0.005	***	(0.001)
Productivity stars	–0.010		(0.010)	–0.013	**	(0.000)	–0.023	*	(0.008)	–0.008	†	(0.004)	–0.022	*	(0.010)
Integrators–power				0.003	*	(0.000)				0.006	***	(0.001)			
Integrators–reach				0.005	***	(0.000)				0.005	***	(0.001)			
Connectors				0.009	***	(0.000)				0.013	***	(0.002)			
Star integrators–power							–0.008		(0.01)				0.002		(0.014)
Star integrators–reach							0.040	***	(0.01)				0.040	**	(0.017)
Star connectors							0.028	***	(0.010)				0.037	*	(0.016)
Int–power × int–reach										–0.009		(0.013)	0.005		(0.010)
Int–power × conn										–0.025		(0.020)	–0.006		(0.008)
Int–reach × conn										0.003		(0.024)	–0.011		(0.016)
Wald χ^2	3593.67***			18116.49***			7497.86***			4001.69***			4602.05***		
Obs./groups	2,441/106			2,441/106			2,441/106			2,441/106			2,441/106		

Note: One-tailed tests for hypothesized effects and two-tailed tests for control variables. Bootstrapped standard errors are in parentheses.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

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Table 6
Fixed-Effects Negative Binomial Regression Predicting Firm-Level Patent Citations (With Bootstrapped Errors)

Variable	Model 1			Model 2			Model 3			Model 4			Model 5		
Constant	0.580	***	(0.180)	0.600	***	(0.180)	0.600	***	(0.230)	0.621	***	(0.190)	0.605	***	(0.186)
Year effects	Incl.	***		Incl.	***		Incl.	***		Incl.	***		Incl.	***	
Patent count	0.003	*	(0.000)	0.001		(0.000)	0.003	†	(0.002)	0.001		(0.001)	0.003	*	(0.001)
Merged	0.001		(0.100)	0.018		(0.080)	–0.018		(0.093)	0.035		(0.092)	–0.014		(0.106)
EU	–0.361		(0.280)	–0.321		(0.250)	–0.333		(0.246)	–0.326		(0.248)	–0.325		(0.238)
US	0.455	†	(0.240)	0.403	†	(0.220)	0.418	†	(0.217)	0.403	†	(0.217)	0.422	†	(0.234)
Pharma	–0.424	*	(0.210)	–0.409	*	(0.190)	–0.415	†	(0.242)	–0.429	*	(0.218)	–0.425	†	(0.240)
Exploration alliances	0.002		(0.010)	0.010		(0.010)	0.009		(0.011)	0.008		(0.011)	0.009		(0.010)
Exploitation alliances	0.019		(0.010)	0.005		(0.010)	0.005		(0.010)	0.008		(0.014)	0.006		(0.011)
Acquisitions	–0.036		(0.020)	–0.026		(0.020)	–0.023		(0.018)	–0.025		(0.020)	–0.024		(0.020)
Biotech patents	0.003	†	0.000	0.003	*	(0.000)	0.003	*	(0.001)	0.002		(0.001)	0.003	†	(0.002)
Biotech focus	0.071		(0.040)	0.064		(0.050)	0.072	†	(0.044)	0.073	*	(0.037)	0.073	*	(0.032)
Network size	0.000		(0.000)	–0.001	***	(0.000)	0.000		(0.000)	–0.001	**	(0.000)	0.000		(0.000)
Network density	0.054		(0.700)	0.196		(0.810)	0.059		(1.026)	0.201		(0.633)	0.058		(1.227)
Average coinventors	0.007		(0.010)	0.005		(0.010)	0.006		(0.021)	0.005		(0.012)	0.006		(0.016)
5-year inventors	0.000		(0.000)	0.001	*	(0.000)	0.000		(0.001)	0.001		(0.001)	0.000		(0.001)
Annual inventors	0.003	**	(0.000)	0.004	***	(0.000)	0.003	***	(0.001)	0.004	***	(0.001)	0.003	**	(0.001)
Productivity stars	–0.017	**	(0.010)	–0.018	**	(0.010)	–0.036	***	(0.001)	–0.012	†	(0.007)	–0.036	***	(0.009)
Integrators–power				0.007	**	(0.000)				0.009	**	(0.003)			
Integrators–reach				0.004	**	(0.000)				0.003	†	(0.002)			
Connectors				0.014	***	(0.000)				0.018	***	(0.003)			
Star integrators–power							0.013		(0.013)				0.017		(0.023)
Star integrators–reach							0.042	***	(0.010)				0.047	***	(0.017)
Star connectors							0.044	**	(0.019)				0.049	***	(0.015)
Int–power × int–reach										–0.005		(0.017)	0.002		(0.010)
Int–power × conn										–0.027	†	(0.020)	–0.002		(0.020)
Int–reach × conn										0.009		(0.040)	–0.009		(0.010)
Wald χ^2	2735.35***			7717.81***			8531.65***			16653.11***			2479.87***		
Obs./Groups	2,441/106			2,441/106			2,441/106			2,441/106			2,441/106		

Note: One-tailed tests for hypothesized effects and two-tailed tests for control variables. Bootstrapped standard errors are in parentheses.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

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associated with firm-level patents claims, which we used as an alternative measure of quality, thus providing further support for the two hypotheses advanced above.[5] Each type of relational stars is also positively and significantly associated with the 5-year (rolling window) counts of patent counts, citations, and claims, which we used as alternative dependent variables, thus providing further support for Hypotheses 1 and 2.[6]

When estimating the regression models with fixed-effects least squares (with robust errors), we found that integrators–power are positively and significantly associated with citations ($p < .10$) but are not significant for patent counts, integrators–reach are positively and significantly associated with patent counts ($p < .001$) and citations ($p < .05$), and connectors are positively and significantly associated with patent counts ($p < .01$) and citations ($p < .01$).[7] When estimating the models with fixed-effects Poisson (with robust errors), we found that integrators–power are positively and significantly associated with patent counts ($p < .10$) and citations ($p < .01$), integrators–reach are positively and significantly associated with patent counts ($p < .01$) but not significant for patent citations, and connectors are positively and significantly associated with patent counts ($p < .001$) and citations ($p < .001$).[8] These alternative estimation methods should be treated with caution as the negative binomial estimation is the best fit for our data.

We also ran robustness checks with different cutoff points for the relational stars so that they can be 2% and 1% of the total number of inventors, instead of 5%. The main patterns in the results remained unchanged.[9] Other robustness checks revealed no evidence of a possible nonlinear relationship between relational stars and dependent variables. Finally, our results remained unchanged even with the dependent variables lagged as right-hand-side variables that proxy for the effects of roles on annual change in our dependent variables. Taken together, all these alternative specifications provided additional and consistent support for Hypotheses 1 and 2.

Discussion

We attempted to extend current research on the role of human capital as a source of firm-level knowledge-based advantage. In particular, we developed theory on structural individual microfoundations of innovation. We emphasize the importance of a relatively neglected set of individual skills manifested by relational stars. We moved beyond existing research focusing mostly on individual productivity, which may have obscured the importance of other critical individual skills in driving firm performance heterogeneity. Innovation is increasingly a team-based endeavor (Wuchty et al., 2007) and is often an outcome of knowledge recombination from existing knowledge stocks (Fleming, 2001). To identify individual roles more likely to effectively execute innovation-generating activities, we applied social network- and knowledge-based thinking to intraorganizational collaborative networks emerging through copatenting individual efforts. Conceptualizing innovation as a process of recombinant search, we argued for the critical role of two individual types: integrators and connectors. We argued that firms with integrators and connectors in their network enjoy a knowledge advantage when it comes to the quantity and quality of their innovation output.

We introduced the term "relational stars" to describe integrators and connectors to highlight the social and collaborative nature of their individual capacities. We thus depart from the traditional focus on productivity stars and emphasize the role of relational stars as

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collaborative outliers. Integrators are the individuals who have a large and dense or expansive network of collaborative ties. Sourcing knowledge from many alters, integrators have the capacity to explore for a great number of alternative knowledge combinations and select the most promising among them. Connectors are the individuals whose collaborative ties span structural holes in their organization's knowledge network and at the same time link unconnected and distant clusters of knowledge. Their broad view of the knowledge network allows them to experiment with novel and diverse knowledge recombinations.

We described how relational stars with their extreme patterns of collaborative behavior end up occupying key network positions in their firm's network that make them consequential for the inventive performance of the firm as a whole. We explained how and why the presence of relational stars translates into firm-level outcomes beyond individual-level outcomes. We argued that because of their collaborative behavior they can become more effective themselves at knowledge recombination, they have the capacity to make others around them more effective at recombination by pointing to promising avenues. Relational stars can also create the conditions (like increasing the network's density or heterogeneity) for more and better recombination to occur. We expanded our theory of relational stars to include "true" relational stars that occupy strong network positions and also exhibit extraordinary individual productivity. The results provided ample support to our theory. Relational stars were positively associated with both quantity and quality of inventive output across alternative dependent variables and different estimation methods. As a result, we showed that relational stars do provide a knowledge-based advantage to their firms.

Our findings have significant implications for the emerging literature on individuals as the microfoundations of organizational capabilities (Felin & Foss, 2005). First, we were able to show that at least when it comes to innovation, certain individuals exhibit patterns of collaborative behavior that make them potentially valuable as sources of organizational capabilities to generate more and high-quality inventions. As a result, we found that there is another set of individuals beyond productivity stars that can provide firms with a knowledge-based advantage. Our approach is qualified to be categorized under the emerging agenda for "microfoundations" research in strategic management as it meets all the necessary requirements as they were recently described in Barney and Felin (in press).

More important, these individuals affected innovation outcomes without being necessarily extremely productive themselves. Instead, it was their collaborative behavior that provided them with opportunities for firm-level impact. That collaborative behavior depends on a complex network of within-firm interpersonal interactions. Therefore, any advantage coming from it is highly firm specific, causally ambiguous, and socially complex (Dierickx & Cool, 1989). As a result, these individuals can be prime candidates as sources of sustainable knowledge-based advantage (Campbell, Coff, & Kryscynski, 2012), especially when compared with the highly visible and easily identifiable productivity stars (Peteraf, 1993). Our results became stronger when these network stars were also productivity stars. Interestingly, we found that in our sample simple productivity stars were negatively related to firm-level knowledge outcomes. Possible explanations for this result include the idea that the existence and pursuit of stars can glorify outsiders and demotivate insiders (Pfeffer, 2001) or the idea that stars are so much sought out by others that they experience information overload and decreasing performance (Oldroyd & Morris, 2012). Based on our results, it seems that productivity stars can have a positive effect on their firms only if they also occupy important network positions. In addition, prior work has provided some evidence for the notion that the impact of star scientists on innovation might be fully mediated by nonstars scientists

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(Rothaermel & Hess, 2007), highlighting the importance of organization-specific complementary assets necessary for superior (team) performance (Groysberg et al., 2008).

This study has some implications for research on intrafirm knowledge networks. Prior research has documented that position of individuals in networks matters for their own individual outcomes and that the structure of the network affects network outcomes. Here, we documented how micro-level network phenomena can translate into macro-level network outcomes. In particular, we showed how the presence of individual nodes in a network (relational stars) affects network-level outcomes (innovation output, both quantity and quality). Two recent reviews on the topic suggested that such efforts are needed to further understand multilevel network phenomena (Brass et al., 2004; Ibarra et al., 2005). To contribute to our understanding thereof, we theoretically and empirically defined our relational stars as outliers in some meaningful network metrics not relatively to their peers in the same network but relatively to all individuals in the population of competing organizations' networks. Furthermore, we explained how the presence of relational stars translates into firm-level outcomes. We thus extended current thinking about the importance of centrality and brokering behavior.

Limitations and Future Research

As every study, this one has its own set of limitations. We relied on copatenting to build internal knowledge networks. We submit that this assumption is a valid one because prior research shows that copatenting involves significant knowledge flows (Singh, 2005). Moreover, there is a possibility that relational stars may not be active in knowledge creation but are listed in patents because of their functional role (i.e., heads of labs). Although we are not able to completely rule this out entirely, there is evidence that it is unlikely: The descriptive statistics on relational stars suggest that these are not extremely productive individuals (i.e., not simply listed in many patents). In addition, we remain agnostic as to the origins of relational stars. Individuals may become relational stars because of their own ability (Lee, 2010) or interfirm mobility or, alternatively, because of firm-specific structures or incentives. We suggest that studying the emergence of relational stars is a promising avenue for future research.

We also make an assumption here that the different types of relational stars have similar effects on outcomes. Similar to the notion of strategic equifinality demonstrated in prior research (Cockburn, Henderson, & Stern, 2000), we focus on the underlying theoretical mechanisms that different relational stars play. Moreover, the observation that relational stars can be created by organizational structures, processes, and routines opens the door for interesting future research extensions. What can firms do to identify or internally develop them? What are the origins of relational stars? These are individuals who had both the ability and opportunity to become relational stars. Therefore, future research can identify contexts that create opportunities for internal development of relational stars by training (Hatch & Dyer, 2004), incentives (Kaplan & Henderson, 2005), alliances or acquisitions (Paruchuri, 2010; Paruchuri, Nerkar, & Hambrick, 2006), human resource practices (Adler, Goldoftas, & Levine, 1999), or corporate culture logics (Felin, Zenger, & Tomsik, 2009).

Finally, we suggested that relational stars are a type of resource with the potential to offer sustainable competitive advantage because of their firm specificity and social complexity. These are properties that they derive from their embeddedness to firm-wide knowledge

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networks. As a result, it might be harder for relational stars to appropriate the value that they add when compared to visible productivity stars. Scholars have argued that individuals with high levels of social capital may be able to appropriate at least some of the added value because of the social capital adding credibility to their claims (Blyler & Coff, 2003), a view that can be consistent with our arguments depending on the comparison group. For example, star integrators are probably best positioned to appropriate their value due to their high human and social capital, with connectors being arguably the least able to appropriate their value. In any case, this remains a limitation of our study, as we simply do not observe the capacity of individuals to appropriate their value. On the other hand, this also becomes a fascinating question for future research.

Managerial Implications

The notion of relational stars not only contributes to our understanding of the sustainability of human-capital-based competitive advantage but also has potential managerial implications. In 1997, McKinsey & Company coined the term "war for talent" to describe the phenomenon of companies trying to attract, hire, and retain the best people. Scholars saw "talent raiding" or "talent poaching" (Cappelli, 2000; Gardner, 2002, 2005) becoming the norm among competing organizations. Today, the situation is even more pronounced for companies whose performance relies heavily on innovation. Competing for stars has become so intense in tech companies that Businessweek (2011) described the phenomenon as "Techdom's Talent Poaching Epidemic." A recent report by PwC's Health Research Institute states that "fifty-one percent of life science executives, the highest of 19 sectors, report that hiring has become more difficult than before, with only 28% saying they're very confident they'll have access to top talent" (PWC Health Research Institute, 2013). Productivity stars may be valuable and rare, but their capacity to provide their firms with sustainable competitive advantage is limited because of their visibility and effortless identification. Other firms can see them and hire them away, thus the "stars" are frequently appropriating their market value (Peteraf, 1993).

Relational stars, in contrast, are hidden in their firm's complex network of interactions in a classic case of cospecialization of assets that increases their firm specificity. Any effects relational stars have on firm-level performance are difficult if not impossible to decipher from the outside because they are socially complex (Dierickx & Cool, 1989). If they indeed have a positive effect on firm-level innovation as our study suggests, then relational stars offer these specific knowledge advantages while remaining relatively invisible and/or less valuable in the external labor market. They may also recognize that their skills have higher value as part of their current network firm. In other words, their firm specificity is increased by both demand- and supply-side mobility constraints (Campbell et al., 2012), mitigating some of the hazards of basing firm-level competitive advantage on human capital (Coff, 1997). In particular, there are significant implications for the appropriation of rents coming from such valuable and rare human capital. Productivity stars are aware of their value, and because of their visibility they can readily appropriate the generated rents the same way that famous sports stars secure contracts loaded with millions of dollars and many years of guaranteed compensation (Rosen, 1981). On the other hand, relational stars are less likely to be able to appropriate all or even most of their generated value because of the complex and firm-specific nature of their added value.

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Received wisdom suggests that individual productivity is the most important skill for innovation and therefore managerial incentive structures are often built to maximize effort and productivity. Our study suggests that the sole focus on productivity, effort, and star knowledge workers may be misleading. First, innovation is a deeply social process of knowledge recombination and collaborative skills are required for effective execution. Second, star workers are in limited supply and therefore come with important caveats: They may appropriate all of the value they create, leave the organization, and transfer their knowledge to competitors, and they are pretty visible to the market and therefore more likely to be hired away. In addition, except for their ex ante identification, there is little else managers can do to internally build them.

Relational stars, in contrast, are free from these weaknesses. First, they are not in limited supply: Relational stars can be identified ex ante or developed internally through encouragement of collaboration. Second, individuals whose performance depends on interactions with others cannot transfer easily their performance to other organizations (Groysberg et al., 2008). Third, individual collaboration generates spillovers (Oettl, 2012), and therefore firms can internalize these externalities and avoid full value appropriation by the individuals involved. In addition, they are less visible to the market because of their embedded nature in the organization's knowledge networks that it becomes less likely for them to become the target of competition. Finally, managers can design practices, incentives, structures, or reward schemes to internally develop relational stars. They can do that by incentivizing the collaboration and knowledge sharing among employees, and thus develop internally the skills of their human capital resources that may remain untapped otherwise. Instead of simply overemphasizing the importance of human capital retention, organizations increasingly need to switch some attention toward developing and then retaining their internal social capital (Dess & Shaw, 2001).

We hope that future research will take up the challenge and produce stimulating work in the fruitful intersection of human resource management, organizational behavior, and strategic management. This not only should allow us to derive more holistic approaches to explaining firm-level heterogeneity, but also will likely lead to important managerial implications on how to manage organizations more effectively.

Notes

1. As a robustness check, we also estimated our models with 5-year patent counts, citations, and claims instead of the annual counts. Our results were the same. We report minor differences, if any, in the results section.

2. Obviously, there is no natural foundation to empirically define our relational stars and any empirical operationalization may seem unavoidably arbitrary. Our guiding principle was to closely follow our theory, experiment with our options, and run many robustness checks to maximize the confidence in our results. We experimented with a number of alternative empirical definitions for integrators. We removed the density and more-than-one-patent requirements, and we used various cutoff points relying on both different percentiles (1%, 2%, 5%, etc.) and distributional metrics (means plus one, two, or three standard deviations). Our main results remained robust to alternative empirical operationalizations. We decided to report the results that utilize the percentile-based definitions (top 5%, top 2%, top 1%) rather than the distribution-based ones (mean plus one, two, or three standard deviations). The reason is that in this way we managed to free our definition from extreme outliers (which would adversely affect distribution-based definitions) and were able to control for the number of individuals characterized as relational stars to facilitate interrole comparisons. Therefore, we chose the cutoffs with an eye toward having similar numbers of integrators–power, integrators–reach, and connectors in each 5-year time window. Again, that was done to simply facilitate interrole comparisons. We report the results for which relational stars are almost 5% of the total number of

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inventors in the network. We ran robustness checks where relational stars were 2% and 1% of the total number of inventors, and our main results remained robust. The previous conversation suggests that we chose the cutoff point for integrators–reach to capture a number of such actors as close as possible to the number of integrators–power. For example, if in a specific 5-year window, our percentile-based definition for integrators–power resulted in 200 of them across all firms, then we chose the cutoff point for integrators–reach to be such that results in as close as possible to 200 integrators–reach. To make things even more clear, we submit the following numerical example. Let's assume there are 1,000 inventors across all firms in the same 5-year time window. They have a varying number of ties with other inventors ranging from 0 to 30 ties. Let's also assume that for an inventor to be at the top 100 inventors in terms of ties (top decile of the tie distribution is what we first sample on) he or she should have 22 ties. Therefore, first we keep only inventors with at least 22 ties. Among those 100 inventors with 22 or more ties, there are some whose alters are all connected to each other (100% density), some whose alters are completely isolated from each other (0% density), and other levels of density in between 0% and 100%. We keep the 50 inventors (top half as we stated earlier in the article) with the higher density ego network levels, and we characterize them as our integrators–power. We then see in which firms these 50 inventors are and create the firm-level independent variables. As a result, we end up with a group of integrators–power who are 5% of the total number of inventors (50 out of 1,000, in this imaginary example). We then take the top 50 inventors in terms of reach to come up with our integrators–reach, and as a result we make sure that their numbers are similar in magnitude.

3. We also experimented with a number of alternative empirical definitions for connectors using theory as our only guiding principle. Using the nbroker measure (measuring the extent of brokerage behavior) instead of density was essentially the same thing. These two measures are simply mirror images of each other since they measure the same thing coming from different perspectives. Nbroker measures structural holes by dividing brokerage by the number of brokerage opportunities (which is a function of ego network size). Density measures structural holes by dividing existing ties by possible ties (therefore measuring the percentage of structural holes that are not there). The only difference between the two measures is that apparently structural holes increase as nbroker increases while density decreases. In addition, before applying our subsequent cutoffs we first selected inventors with more than two ties; this is the minimum number of ties after which the measures of density and brokerage can be meaningfully defined. As in the case of integrators, we experimented with various percentile cutoffs and distributional cutoffs. Again, we chose to report percentile cutoffs to control the number of connectors as relational stars and have them as close as possible to the number of integrators. Our main results remained robust. We report the results where connectors are almost 5% of the total number of inventors; the results for 2% and 1% remained robust.

4. We used the countfit function in Stata, which compares the fit between different estimation methods and the data, and the results confirmed that negative binomial was a better fit for our data than Poisson.

5. Integrators–power ($p < .01$), integrators–reach ($p < .001$), and connectors ($p < .001$) were all positively associated with firm-level patent claims. Results are available from the corresponding author upon request.

6. Integrators–power ($p < .001$ for counts, citations, and claims), integrators–reach ($p < .001$ for counts, citations, and claims), and connectors ($p < .001$ for counts, citations, and claims) were all positively associated with the 5-year firm-level counts of patent counts, citations, and claims. Results are available from the corresponding author upon request.

7. In the fixed-effects least squares estimation, integrators–power ($p < .001$ for patent counts, citations, and claims), integrators–reach ($p < .001$ for patent counts, citations, and claims), and connectors ($p < .001$ for patent counts, $p < .01$ for patent citations, $p < .05$ for claims) were all positively associated with the 5-year firm-level counts of patent counts, citations, and claims.

8. In the fixed-effects Poisson estimation, integrators–power ($p < .05$ for patent counts, $p < .001$ for citations, and $p < .05$ for claims), integrators–reach ($p < .001$ for patent counts and $p < .01$ for claims), and connectors ($p < .001$ for patent counts, $p < .01$ for patent citations, $p < .05$ for claims) were all positively associated with the 5-year firm-level counts of patent counts, citations, and claims.

9. We estimated our models using three different estimation methods (negative binomial, least squares, and Poisson). Within each one of them, we predicted six different dependent variables (patent counts, citations, claims and 5-year versions of them) using three sets of relational stars (relational stars that are almost 5% of the total number of inventors—we report these results in the tables, relational stars that are 2% of the total number, and relational stars that are 1% of the total number). When estimating the negative binomial models, the results remained the same for all three sets of relational stars (positive and significant for all DVs) with the exception of 1% integrators–reach who were not significant predictors of patent citations. When estimating the least squares models, the results remained the same for all three sets of relational stars (positive and significant for all DVs—except for

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integrators–power and patent counts) with the exception of 1% integrators–reach who were not significant predictors of patent citations. When estimating the Poisson models, the results remained the same for all three sets of relational stars (positive and significant for all DVs—except for integrators–reach and patent citations).

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