Essays on the Micro-Foundations of the Knowledge-Based View: Human Capital, Knowledge Networks and Innovation Strategy

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Essays on the Micro-Foundations of the Knowledge-Based View:
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SUMMARY

I look at knowledge networks emerging through individual collaboration within incumbent firms and I make an effort to identify individual roles that are driving a number of meaningful firm-level innovation-related outcomes. I document how certain individuals occupy such positions in their firms' knowledge network that equip them with unique blends of human and social capital, thus making them consequential for the innovative performance of the system as a whole. Integrators are the actors with an extraordinarily large and dense network of different collaborators. Connectors are the individuals who collaborate with others across diverse knowledge areas and clusters. Isolates are actors who are productive while remaining relatively unconnected and independent. I find that relational stars (i.e. integrators and connectors) positively affect their organization's quantity and quality of inventive output. On the other hand, I find that it is isolates and star inventors who positively affect inventive productivity. I find that individuals with extreme patterns of collaborative behavior (either local or distant) facilitate exploration and that productive isolates drive exploitation. In addition, I find that organizational ambidexterity can be attained by having individuals who can simultaneously explore and exploit or by increasing the connectedness between exploratory and exploitative activities. Finally, I find that knowledge boundary choices are also affected by internal organization and human resource attributes.

CHAPTER 1

INTRODUCTION

The conceptual foundations of this dissertation lie at the intersection of strategy, innovation, human capital, and organizational theory research. Two broad questions drive my inquiry: first, where does innovation come from, that is, where are the origins of new ideas, inventions, knowledge, and products? Second, what can firms do about it, that is, how can managers design the necessary organizational structures, incentive systems, and processes to effectively implement the innovation process? In particular, I attempt to address these questions by looking at the micro-level of analysis and by trying to understand how individual actions and interactions result in firm-level innovation-related outcomes. Therefore, a more focused set of research questions that guides this research relates to the challenge of identifying, organizing, and developing relevant human capital for innovation at the firm level of analysis. Addressing these questions inherently requires an interdisciplinary approach; in this work, I draw insights from different streams as diverse as organizational theory, innovation research, entrepreneurship, networks, knowledge-based view, learning, human capital, economics/sociology of science, and core strategy. In what follows in this chapter, I briefly outline the three main chapters of my dissertation, identify the common thread linking all of them, and highlight the main contributions.

In this dissertation, I look at knowledge networks emerging through individual collaboration within incumbent firms and I make an effort to identify individual roles that are driving a number of meaningful firm-level innovation-related outcomes. A large body of innovation research has focused on the routines, capabilities, or competences that firms need to possess in order to be innovative. Research on the role of individuals as the microfoundations of these capabilities has been much more limited. Even when scholars examine the individual role, the focus has been almost exclusively on the highly productive individuals. However, innovation is a communal team-based endeavor, which depends on knowledge sharing, search, transfer, recombination, and reconfiguration. This simple observation suggests that individuals, who are responsible for implementing these knowledge processes, should possess relational capacities that go beyond simple productivity and that the sole focus on individual productivity may be incomplete.

To address this gap, I examine the combination of productive and collaborative behavior of individuals. I document how certain individuals occupy such positions in their firms' knowledge network that equip them with unique blends of human and social capital, thus making them consequential for the innovative performance of the system as a whole. First, I rely on a typology of critical individual roles. Integrators are the actors with an extraordinarily high number of different collaborators. Connectors are the individuals who collaborate with others across diverse knowledge areas and clusters. Isolates are actors who are very productive while remaining relatively unconnected and independent. The three individual types correspond to alternative knowledge generation paths: local knowledge recombination, distant recombination, and independent knowledge production. Second, I identify the overall structure of a firm's knowledge network capturing important characteristics of the network like its size, cohesion, fragmentation, and certain important individual links. I then link the different individual roles and firm-level knowledge network micro-structures with a number of firm-level innovation-related outcomes: in the three chapters of my dissertation, I examine the effect of individual types and network structures on their firms' inventive output, learning capability, and capability to adapt to a changing technological paradigm.

In the first chapter, I argue that certain individual types are critical drivers of the quantity, quality, and productivity of their firms' inventive output; albeit for different reasons and with different effects. More specifically, I suggest that relational stars (i.e. integrators and connectors) positively affect the quantity and quality of their firm's inventive output. Integrators source knowledge from many others and therefore, have the capacity for effective knowledge recombination characterized by significant variation and strong selection among potential recombinations. Connectors collaborate across knowledge areas and therefore, have the capacity for radical knowledge recombination and inventive trials. On the other hand, I suggest that it is isolates and star inventors who drive of the productivity of their firm's output. Isolates remain independent from the network's knowledge directions and independently generate new knowledge and therefore, supply the firm's knowledge base with new knowledge stocks in an efficient manner (i.e. without having to incur the costs of collaboration and coordination). A similar line of logic applies to the extremely productive star inventors. Overall, in this chapter I establish the importance of different individual roles on direct inventive outcomes of their firms.

In the second chapter, I explore the effect of these individual types on their firm's capacity to learn and renew its knowledge base. In particular, I develop a theory about the role of different role-sets of individuals in exploratory or exploitative learning and in addressing inherent trade-offs in the pursuit of organizational ambidexterity. I argue that relational stars (i.e. integrators and connectors) drive exploratory output because of their capacity to recombine knowledge from many different sources while isolates are the ones driving exploitative output because of independently building knowledge in depth without any interpersonal knowledge recombination. I then turn to the question of how a firm attains both exploratory and exploitative output. I hypothesize that in order to be able to do both, a firm relies on individuals who can do both and alternatively on direct collaborative paths between individuals who are good at exploration and individuals who are good at exploitation. The underlying idea is that in order to do both, a firm should be good at selecting and transferring knowledge produced at exploratory activities to the existing knowledge base in order to be further recombined and incrementally improved. As a result, I highlight the role of certain individuals as the microfoundations of exploration and exploitation and challenge conventional wisdom around the need for organizational separation when it comes to the pursuit of organizational ambidexterity. In essence, this chapter takes the idea of different individuals contributing generally to inventive output a step further, showcasing how the various individual roles may be more important for certain learning outcomes. In addition, in this chapter I examine how the structure of the knowledge network affects the capacity of firms to concurrently generate radically new knowledge and incrementally new knowledge.

In the third chapter, I build on this idea of internal networks, individuals, structures affecting a firm's inventive output and I examine how the state of internal capabilities affects the effectiveness of external knowledge sourcing when it comes to adaptation to a changing technological paradigm. Under circumstances of disruptive technological change, incumbents have to develop new knowledge and they face a sourcing choice; they will either develop it internally or externally source it (i.e. an R&D alliance). More often than not, firms combine external and internal knowledge sourcing. In this chapter, the main objective is to understand how the structure of a firm's internal knowledge network and the different individual types in it, alter the effectiveness of external knowledge sourcing efforts. I suggest that the structure of the internal network and the individuals in it can tell us something about the firm's potential for future knowledge recombination and the state of internal coordination costs in the knowledge generation process. In turn, these two factors alter the effectiveness of external knowledge sourcing. External sourcing in the form of alliances and acquisitions can be costly. Therefore, I hypothesize that combining internal and external sourcing is less effective when the firm has the capabilities to generate new knowledge in the new paradigm internally or has an already high level of internal coordination costs, and vice versa.

In this dissertation, the general setting is the global pharmaceutical industry. I follow a largely representative sample of incumbent firms for a period of 25 years. I rely on their patent portfolio to develop internal knowledge networks emerging through individual co-patenting events. I use the UCINET software to capture network metrics for individual inventors, identify the various individual types, and capture certain properties of the firm's internal knowledge network. I add firm-level innovative activities (e.g. alliances, acquisitions, etc.) to control for other drivers of innovative outcomes and show the additional effect of individuals and knowledge structures.

The major contribution of this dissertation is the development of 'left-hand' side explanatory variables that affect well-known firm-level inventive outcomes. I rely almost exclusively on the knowledge-based view as my conceptual lens to explain the generation of new knowledge in firms. I then explain how certain individuals and network micro-structures affect the performance of the process of new knowledge creation. As a result, I contribute to the emerging theme of 'microfoundations' research in strategic management, and I make an effort to show how certain individual types and knowledge network micro-structures can be viewed as the micro-level determinants of the performance of the firm as a whole. In the process, I make several contributions to other lines of research. I extend research on social networks by making the link between the micro and the macro. I show how node-level properties (individual level positions) translate into macro-level outcomes (the performance of the network as a whole). In addition, I extend research of human and social capital by showing how individual-level social capital becomes human capital for the firm. Further, I contribute to existing theories of organizational learning by uncovering some micro-origins of learning performance and by highlighting the individual role in firm-level ambidexterity. Finally, I extend research on governance choices for capability building by showing how firms can effectively combine external knowledge sourcing with internal capabilities for capability building in a new technological space.

CHAPTER 2

STRUCTURAL MICROFOUNDATIONS OF INNOVATION: THE EFFECT OF RELATIONAL STARS ON INVENTIVE OUTPUT AND PRODUCTIVITY

2.1. Introduction

Since Schumpeter (1942) we have known that innovation is a vehicle of economic growth and a source of firm performance heterogeneity. Research on the antecedents of innovation has extensively focused on the innovative capabilities that firms need to develop in order to initiate or respond to frequent technological change. Organizational 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) of transforming existing knowledge into something new. The simple observation that knowledge is the key raw material for innovation (Nonaka, 1994) combined with the recognition of individual actions and interactions as the realistic locus of knowledge (Felin & Hesterly, 2007), directed attention to the role of individuals as the microfoundations of the necessary capabilities (Felin & Foss, 2005). Indeed, research indicates that the so-called ‘star knowledge workers’ or ‘star scientists’, bring several benefits to their organizations (Groysberg, Lee, & Nanda, 2008; Lacetera, Cockburn, & Henderson, 2004; Rothaermel & Hess, 2007; Zucker, Darby, & Brewer, 1998). As a result, there is a significant degree of consensus that productivity stars matter for organizational knowledge outcomes. However, we still have a gap in our understanding with respect to other individual roles and relational skills that are perhaps equally important for the effective implementation of the knowledge production process.

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). Consequently, individuals should also possess the necessary social and collaborative skills to effectively implement these socially-intensive knowledge sub-processes. In this paper, we make an effort to identify these actors by looking for extreme patterns of individual collaborative behavior. Applying network thinking, we argue for the positive effect of two individual structural roles on the inventive output of their organizations. We refer to them as 'relational stars' to emphasize the social aspect of their skills, to depart from traditional 'productivity stars', and to highlight their nature as outliers in terms of collaborative behavior. More importantly, we extend our current understanding of the effect of productivity stars on the quantity of inventive output and provide our first contribution by highlighting the role of relational stars as the structural microfoundations of both the quantity and quality of their firm's inventive output. In essence, we argue that these actors can exploit their patterns of 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 also explain how the presence of such individuals in a firm's network translates into firm-level knowledge outcomes by making every actor around them more effective in producing new knowledge.

In particular, we focus on two types of relational stars: integrators and connectors. Integrators are the actors who have a large dense network of collaborators and therefore have the capacity to integrate and recombine knowledge from many different sources. Connectors are the individuals whose collaborative behavior facilitates bridging of structural holes; they operate as the linking pins among internally distant and otherwise unconnected clusters of knowledge and therefore have the capacity to engage in high risk and radical trials of knowledge recombination. In addition, we identify a third important type of individuals whose behavior makes them the opposite of relational stars. We look at isolates, individuals who produce new knowledge while unconnected from their organization's network and therefore have the capacity to infuse the knowledge base with diverse perspectives as they are the least affected from the organization's knowledge directions. Conceptualizing invention as a search process of knowledge recombination (Fleming, 2001), the three types correspond to three alternative paths: local recombination, distant recombination, and independent knowledge production. We rely on both conceptual arguments and empirical techniques to justify the identification of these three distinct individual roles. Interestingly, all three individual roles become important for firm-level inventive output not because they are necessarily productive, as is the case for simple productivity stars, but mainly because their collaborative behavior facilitates effective recombinant search or generation of diverse new knowledge. It is important to note here that if these types of actors are defined relative to their peers in an organization's internal network, then every organization would have its own share of relational stars. Instead, we define relational stars relative to their counterparts in every competing organization's network looking for outliers in two important dimensions:

centrality and bridging behavior.

This approach follows existing research on 'star scientists' where stars are the actors at the top of the productivity distribution of all scientists across firms. More importantly, this approach allows us to provide a second significant contribution. Research on networks has unveiled that an individual's position in the internal network may affect that individual's involvement in innovation (Obstfeld, 2005), creativity (Fleming, Mingo, & Chen, 07), 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 with respect to the effect of nodes in certain positions on the overall network's performance. Authors of a recent review on network research suggest that micro-to-macro gap remains (Kilduff & Brass, 2010). With this study, we make an effort to document the mechanisms through which the mere presence of an individual position (that is, a certain pattern of individual collaborative behavior) may affect not only that individual's performance but also the performance of the network as a whole.

Finally, we provide another significant contribution to the emerging literature on individuals as the microfoundations of organizational capabilities. To do that, we explore for the impact of different individual roles on a number of meaningful knowledge outcomes: the quantity, quality, and productivity of firm-level inventive output. We find that although both types of relational stars positively affect their firm's quantity and quality of inventive output, they do not have similar effects on inventive productivity. Instead, it is the isolated individuals and the traditional productivity stars that seem to drive their organization's knowledge productivity. As a result, we provide theory and evidence about the heterogeneous organizational knowledge benefits stemming from different individual roles.

2.2. Theory and Hypotheses

Organizational research on the antecedents of knowledge generation has 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 (Kogut & Zander, 1992) spurred significant research efforts linking capabilities directly to organizational knowledge outcomes (Henderson & Cockburn, 1994; Kogut & Zander, 1992; Teece et al., 1997; Zollo & Winter, 2002). However, early research in the knowledge-based paradigm emphasized the importance of accounting for individuals in order to clearly understand the formation of such organizational capabilities (Conner & Prahalad, 1996; Grant, 1996; Nonaka, 1994). The problem is that macro-level explanations that link capabilities with outcomes without considering individuals as their microfoundations open the door for alternative micro-level explanations (Abell, Felin, & Foss, 2008). Theoretical support of individuals as the realistic locus of knowledge (Felin & Hesterly, 2007) channeled some research towards the role of human capital in driving organizational innovation. Evidence suggests that firms enjoy several benefits when they employ 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).

However, if we want to understand the role of individuals as drivers of firm-level knowledge outcomes and we only focus on individual productivity without considering the origins of that productivity, then our understanding of the phenomenon remains incomplete. A first gap exists because we neglect to take into consideration the fact that individual creativity has an apparent social side (Perry-Smith & Shalley, 2003). Early research on the emergence of industrial R&D suggested that an advantage of the industrial research laboratory was that "it could take several men, 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). Organizations have an advantage over individuals because they can internally develop intellectual capital based on social interactions among their members (Nahapiet & Ghoshal, 1998). Hence, apart from individual productivity there is a set of social and collaborative skills that is at least as important for new knowledge creation. This importance is even more pronounced in the innovation literature which suggests that innovation is an outcome of a socially intensive process of knowledge transformation. Individuals innovate by searching for potential knowledge recombinations between familiar and new components (Fleming, 2001). Socialization (Fleming, 2002) and intraorganizational persuasion and conflict (Gavetti & Levinthal, 2000) are important components of successful search outcomes. Firms need to integrate disparate pieces of knowledge (Henderson & Cockburn, 1994) and dynamically reconfigure their existing knowledge stocks as markets evolve (Galunic & Eisenhardt, 2001). Knowledge should be reused, recombined, and accumulated to result in innovation (Murray & O'Mahony, 2007). To effectively implement these processes, it follows that individuals should possess relational capacities to collaborate and form extensive knowledge networks.

A second gap exists because we have limited theory and evidence to link individual positions in these networks with firm-level knowledge outcomes. The overall importance of these networks has not been neglected. For instance, there is research documenting 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) and research supporting the effect of the network's overall structure on network-level outcomes (Argyres and Silverman, 2004; Lazer & Friedman, 2007; Tsai, 2002; Yayavaram & Ahuja, 2008). However, although there is some evidence that actors in certain positions affect organizational outcomes (see Nerkar & Paruchuri, 2005), research on the role of individuals in these networks as drivers of network-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).

In this study, we make an effort to address these two gaps by introducing the concept of 'relational stars'. Relational stars are actors with extreme patterns of collaborative behavior. Through their own collaborations combined with the collaborative behavior of their alters, relational stars end up occupying positions in their firms' internal collaborative network that are highly consequential for the performance of the network as a whole. In what follows, we link counts of relational stars with organizational outcomes. The behavioral pattern of a relational star has two components: what the individual can do with the network position which results from his/her collaborative behavior and what the individual is (derived from the position) although the two are closely intertwined. It is also important to note that these collaborative patterns have certain origins beyond individual skills and abilities. Actors emerged in their positions because they were also appropriately motivated to collaborate and were provided with the opportunity to do so by their organization's structures, incentives, or strategies. Disentangling these origins of network positions is beyond the scope of this paper. Here, we only focus on explaining why the presence of relational stars translates into firm-level inventive outcomes. As a result, we address the previously identified gaps by showing that collaborative skills matter at least as much as simple individual productivity and that individuals with extreme collaborative behavior affect not only their own performance but also the performance of the network as a whole.

2.2.1. Integrators

Integrators are the actors who have an extraordinarily large and dense network of collaborators. They are the glue that holds together dense inter-individual knowledge co-creation clusters; normally, these actors 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 widely documented. Centrality is associated with an individual's promotions (Brass, 1984), exercise of power (Ibarra, 1993), supervisor ratings (Mehra, Kilduff, & Brass, 2001), socialization (Morrison, 2002), innovative performance (Cross & Cummings, 2004), involvement in innovation (Obstfeld, 2005), and performance bonus (Gargiulo et al., 2009). However, much less is known with respect to the role of such individuals on the performance of the network as a whole. Here, we link the presence of integrators in an organization's collaborative network with network-level knowledge outcomes. To do that, we define integrators as universal outliers; they are individuals whose collaborative behavior involves a number and density of alters which is large not relative to their peers in their organization's network but relative to all individuals in all competing organizations. We argue that organizations employing such collaborative outliers enjoy an advantage in their inventive output. We choose the term 'integrators' to illustrate their main knowledge function, that is, knowledge integration; the term has been previously used to describe actors who bring people together and fill structural holes (Xiao & Tsui, 2007). In addition, we prefer this term over central actors to emphasize the outlier status of these individuals. Integrators are not just central in their firm's network; their number and density of collaborative ties puts them at the top of the distribution when compared with all individuals from all competing organizations.

At the core, 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 collaborative ties, integrators observe a large number of alters, understand who knows what (Borgatti & Cross, 2003), source knowledge from many actors, and therefore, have the capacity to identify more potential knowledge recombinations. Outliers have a disproportionate advantage in this respect because every additional tie has an exponential effect on the number of potential recombinations. This process of significant variation uniquely equips them to affect the overall *quantity* of their firm's inventive output. In addition, integrators rely on a process of stronger selection: integrators have the capacity to familiarize themselves with many potential recombinations and experiment with them in order 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 inventive 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).

In addition, the presence of integrators in a firm's network makes every actor around them better 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 are building on a knowledge base which includes more and better recombinations which in turn, results in them developing more and betters ones. Further, the presence of integrators creates some conditions that have been shown 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). Overall, integrators have the capacity to integrate knowledge locally for more and high quality recombinations, diffuse the updated knowledge base, and create the conditions for further high quality invention to occur.

Hypothesis 1: The quantity and quality of a firm's inventive output is a positive function of the number of integrators in its collaborative network.

2.2.2. Connectors

Connectors are the 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. Extensive evidence suggests that individuals-brokers 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 which 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. While not necessarily productive or highly collaborative, connectors operate as the 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. We define connectors as actors who span the highest number of structural holes in the network and access the highest share of their network compared to brokers in all other competing organizations' networks.

At the core, the main mechanism through which connectors affect network-level outcomes is their capacity to execute a process of knowledge recombination based on radical variation. Connectors use their ties' knowledge inflows to access diverse, distant, and previously unconnected sources of knowledge. Therefore, they are more likely to identify potentially novel and high quality recombinations. Their capacity to collaborate across knowledge boundaries allows them access to heterogeneous knowledge stocks and engagement in high risk inventive trials. Uncovering links where none existed before allows them to further build on them to identity more and better possible recombinations and eventually positively affect both the *quantity* and *quality* of their firm's inventive output.

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. Further, these alters are not simply part of a dense local network of interactions but belong to a diverse set of knowledge clusters. Therefore, 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 high quality invention. Connectors promote relaxed structures which facilitate improvisation (Brown & Eisenhardt, 1997), network heterogeneity which enables learning (Reagans & Zuckerman, 2001), network range which supports knowledge transfer (Reagans & McEvily, 2003), and decrease the path length between any two actors in the network thus improving its overall performance (Cowan & Jonard, 2003).

Hypothesis 2. The quantity and quality of a firm's inventive output is a positive function of the number of connectors in its collaborative network.

2.2.3. Isolates

Isolates are the actors who belong to the firm but remain unconnected from the organizational knowledge network while being productive enough to be 'at risk' of connecting themselves to the network. They are individuals who produce knowledge independently and are the exact opposite of relational stars. Therefore, we shift attention to actors who may be important for their organization not because of their ties but despite the absence of such ties.

There are reasons to believe that a firm could benefit from such isolates in terms of the quantity and quality of its inventive output. The process of knowledge recombination, especially within intraorganizational knowledge networks, can be viewed as a pursuit for local optima (Gavetti & Levinthal, 2000). Actors collaborate to generate improvements and this process can be self-sustaining and result in significant similarities of knowledge among the actors of the collaborative network as recombinations are communicated through diffusion. Therefore, internal collaborative networks are vulnerable to falling into competency traps (Levitt & March, 1988), a tendency to rely on inferior knowledge spaces when superior alternatives exist. As a result, these networks can greatly benefit from individuals who can infuse some knowledge diversity into the system of knowledge recombination. Such actors should participate in the development of knowledge but be relatively unconnected from the rest of the network to avoid overembeddedness and the risk of social capital (Adler & Kwon, 2002). Isolates do exactly that: they remain unaffected by the network and have the capacity to provide the knowledge base with some much needed diversity. Knowledge provided by isolates enters the firm-wide recombinant process when their knowledge gets picked up by individuals who belong to the network and this is when the benefits of knowledge diversity are realized.

However, a more obvious firm-level knowledge outcome that is clearly positively affected by the presence of isolates is the productivity of a firm's inventive output, defined in the typical economic sense of outputs divided by inputs. Isolates are very efficient knowledge creators. Without having to collaborate with anyone else, and without having to incur the communication and coordination costs associated with collaboration, isolates have to capacity to create new knowledge independently. Therefore, organizations with isolates benefit both from the creation of new knowledge and diverse additions to their knowledge base at the lowest possible level of coordination costs. They receive output using with the minimum level of input. What really differentiates isolates from all other actors (including relational stars) is this unique ability to produce knowledge while unconnected from the network and therefore positively affect their organization's productivity of inventive output. However, at the same time this discussion suggests that relational stars who rely on a large number of knowledge sources to recombine and generate new knowledge should be negatively related with the overall firm's inventive productivity. This effect should be even more pronounced for integrators who exist because of large and dense networks of collaboration.

Hypothesis 3. The productivity of a firm's inventive output is a positive function of the number of isolates in its collaborative network.

Hypothesis 4. The productivity of a firm's inventive output is a negative function of the number of integrators in its collaborative network.

Before proceeding with our methods designed to test our hypotheses, we believe it is important to first conceptually justify why we chose to focus on these three individual roles and why they are also conceptually distinct. First of all, the literature on networks has extensively studied three critical aspects of an individual's network position: centrality, brokerage, and isolation. Several studies have documented the positive effect on individual-level outcomes when individuals occupy such positions. Therefore, the first reason why the roles are three is prior work on networks. However, we also depart from prior work and choose different names and additional requirements (beyond simple centrality and brokerage) for our relational stars because we seek to understand their effect on firm-level knowledge outcomes. There is a clear conceptual reason why actors need to satisfy additional requirements in order to have firm-level outcomes. Integrators need both many ties and high density to have the hypothesized firm-level effects through a strong evolutionary cycle of recombination, constant diffusion, and favorable conditions for invention to occur. Similarly, 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. As it should be evident from the different theoretical mechanisms and prior work on networks the two types of relational stars are also conceptually distinct from each other.

Finally, the three individual roles are also conceptually distinct from simple firm-level average phenomena. First, our typology of relational stars relies on capturing 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 which on average is highly centralized and dense without having a single integrator-outlier. Similarly, one can observe a firm-wide knowledge network which is on average highly fragmented without identifying a single connector-outlier. Interestingly, identifying these outliers 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 execute effectively the processes of recombination, diffusion, etc. through which they have their main effects on firm-level knowledge outcomes. The number of isolates is obviously unrelated to any firm-level phenomenon. 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. This is why we follow an empirical design where we control for network size and other firm-level actions that have been already shown to affect inventive output at the firm level.

2.3. Methods

To test the developed hypotheses, we followed a longitudinal research design in the global pharmaceutical industry. Firms in this industry are under constant pressure to continuously 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 in order to survive. To respond, pharmaceutical firms engaged in a wide array of alternative strategies to remain innovative; they took on alliances, acquisitions, heavy investment in internal research, and in human capital to build or maintain innovative capabilities (Rothaermel & Hess, 2007). Therefore, the pharmaceutical industry is an ideal setting for this paper to explore for the role of relational stars in driving inventive output above and beyond the mentioned innovation levers. Our observation period is from 1974 to 1998. Our sample consists of 106 pharmaceutical firms that were active in the production of human in-vivo therapeutics and were founded before 1974. 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. Horizontal mergers are a common incident in this industry; when a merger occurs we combine the data of the merging firms into one entity, we continue tracking it forward, and we create an indicator variable to capture a merged entity.

We constructed the key dependent and independent variables relying on patents granted to these firms by the USPTO. Despite some problems, patents have been extensively used to measure a firm's innovative activities (e.g. Ahuja, 2000; Henderson & Cockburn, 1994). In addition, the pharmaceutical industry is the industry which 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 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 have each firm's full patenting. From resulting patent portfolios, we kept information about dates of applications, citations received, claims made, inventors listed, and assigned technology classes. Many firms in our sample are dedicated pharmaceutical firms. However, there are also some diversified conglomerates that are also active in other industries. We argue that knowledge by inventors in unrelated industries has little to do with our knowledge-based arguments. Hence, we sampled on the resulting patent portfolio for every firm and we relied on information from technology classes to keep only patents with a clear chemistry or biology component which are more likely to be related to the technologies underlying human therapeutics.

2.3.1. Dependent Variables

To measure the quantity of a firm's inventive output, we used the annual count of patents granted to our sample firms. To measure the quality of a firm's inventive 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 sample period ends in 1998, we track 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 citations received by a patent is a significant predictor of its market value (Hall, Jaffe, & Trajtenberg, 2005) and has already been used to measure the usefulness of inventions (Yayavaram & Ahuja, 2008). In addition, as a robustness check for the quality of a firm's inventive output, we used the number of claims made by a firm's patents to capture a different dimension of their quality. Claims are arguably a measure of a patent's technical quality and have been used in prior research to measure the quality of a firm's inventive activities (Singh, 2008). Finally, to measure the productivity of a firm's inventive output, we divided the annual count of patents granted to a firm by the number of inventors listed in those patents to create an outputs-to-inputs measure of inventive productivity.

2.3.2. Intrafirm collaborative networks and independent variables

To identify relational stars and create the independent variables for this paper, we developed intrafirm co-inventing networks for each firm from 1974 to 1998. 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 name. When there was still a conflict, we expanded our matching criteria to include city and state of residence for each inventor. The resulting dataset 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 co-inventing networks. Nodes of our networks were individual inventors and ties were co-patenting events among them. Our main argument is that these ties involve knowledge flows and thus, we proceeded by characterizing knowledge through a tie which is older than five years as obsolete. Therefore, we developed the knowledge networks using a five-year rolling window and assigned the resulting values to the last year of each time window (e.g. 1992-1996 values to 1996, 93-97 values to 97, etc.). We analyzed our network and kept a wide array of ego-network metrics to define the three types of relational stars. Then, we constructed three variables at the inventor level:

Integrator. To closely follow our theory, 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, in order 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', that is, 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 five-year window. Then, among the resulting set of actors, we characterized as integrators the 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. Second, to capture integrators we relied on the distribution of the 'two-step reach' metric from UCINET, which measures the percentage of the overall network that an individual accesses with his/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 five-year window.[1]

Connector. In the theoretical part of the paper, we emphasized that connectors are not only knowledge brokers in terms of spanning many structural holes, but they are also individuals who connect distant clusters of knowledge and have access to a large share of their firm's collaborative network. 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 all inventors from all firms during the same five-year time window. Hence, we 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 spanned 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.[2]

[1] Obviously, there is no natural foundation to define integrators. The only guiding principle was to closely follow our theory. As a result, every empirical definition may seem unavoidably arbitrary. Therefore, we experimented with a number of alternative empirical definitions for integrators. We removed the density and more-that-one-patent requirements, and we used various cutoff points relying on both different percentiles and distributional metrics (means plus one, two, or three standard deviations). Our main results remained robust. We decided to report results based on percentiles rather than distributional metrics because in that way we managed to free our definition from extreme outliers and we were able to somehow control for the number of individuals characterized as relational stars. This is important because we didn't want our results to be affected by the mere number of relational stars. Therefore, we made every effort to have similar numbers of integrators-power, integrators-reach, and connectors in each five-year time window. As a result, 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.

[2] 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. 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.

I*solate***.** Empirically defining isolates was a straightforward exercise. The indicator variable '*isolate'* captures inventors with more than one patents in the same five-year time window (to exclude one-time inventors) while unconnected from the firm's network (that is, zero ties). [3]

Using these indicator variables at the inventor level, we developed our independent variables at the firm level using counts of *integrators-power, integrators-reach*, *connectors*, and *isolates*, that each firm possesses in each year from 1974 to 1998 (again counts from time window 74-78 go to 1978, counts from 75-79 go to 79, etc.). It is important to note here that we also empirically confirmed the focus on these three types of individuals. We run 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 which groups together low density and high brokering behavior corresponding to connectors; second, a factor which includes a large number of ties with high centrality corresponding to integrators-power; third, a factor which includes a large number of ties coupled with large two-step reach corresponding to integrators-reach. Isolates are simply the opposite of relational stars.

2.3.3. Control Variables

We included a series of control variables to rule out other factors that have been shown to affect a firm's inventive output. First, we included the *number of total alliances* in our models to control for the effect of alliance activity on inventive output. We collected data on every firm's alliance portfolio from the BioScan directory and the ReCap database,

[3] We also experimented with a number of alternative empirical definitions for isolates. We allowed inventors to have one, two, or three ties with the firm's network to explore for the effect of relative isolation. Main results remained robust even for relative isolates.

data sources that are the arguably the most comprehensive of alliance activities. 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 and focus of firms in the emerging biotechnology paradigm which may also affect their overall inventive output. To identify biotech patents, we relied on the definition of a biotech patent provided by the Patent Technology Monitoring Division (PTMD) of the U.S. PTO. Further, our longitudinal design allowed us to control for temporal effects by including year indicators. Finally, we used controls for merged entities (*merged*) as horizontal mergers are very common in the industry, for national origin (*US and EU*), and for the main industry of each firm's activities as there are diversified firms in our sample with only some presence in human therapeutics (*Pharma*).

More importantly, we included in our models the number of star inventors (*stars*) that each firm possesses. We followed prior research and 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 five-year time window. At the firm level, *stars* is a variable counting the number of star inventors for every five-year window. More importantly, we controlled for *network size* which is arguably one of the main drivers of the development of integrators, connectors, and isolates. The larger the network the more the opportunities for individuals to establish connections and become integrators or connectors and the greater the probability of finding more isolates. Hence, by controlling for network size we run very conservative tests for our hypotheses as we were able to show that integrators, connectors, and isolates all affect inventive output beyond any effect of the overall network size. By including network size we also controlled for the size of each firm and we had a fine-grained measure of research investment in inventive activities.

2.3.4. Estimation

Our main dependent variables (patent counts, citations, claims) are all nonnegative overdispersed count variables. Therefore, we used the negative binomial estimation method which provides a better fit for the data than the restrictive Poisson.[4] Both fixed- and random- effects specifications would allow us to control for any remaining unobserved heterogeneity (Greene, 2003). We run a Hausman test which suggested that there are no significant differences between the two estimation methods. Nevertheless, we chose to rely on a firm fixed-effects specification to conduct a conservative within-firm analysis and control for firm-level unobservable factors. However, as a robustness check, we also used the random-effects specification and our results remained the same. In addition, every model was estimated with bootstrapped standard errors. To estimate inventive productivity, which is not a count variable, we relied on a firm fixed-effects least squares estimation with robust standard errors. Overall, the longitudinal nature of our empirical design, the definition of independent variables using 5-year rolling windows, combined with a rich set of control variables suggest that we did our best to

[4] We also 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 much better fit for our data than Poisson.

address any endogeneity concerns (Hamilton & Nickerson, 2003).[5]

2.4. Results

Table 2.1 (in the Appendix) depicts descriptive statistics and bivariate correlations for our variables. Correlations among our independent variables are below the recommended ceiling of 0.70. To further evaluate the threat of collinearity, we estimated the variance inflation factors (VIFs) for each coefficient, with the maximum estimated VIF being 3.50, which is well below the recommended threshold of 10 (Cohen, Cohen, West, & Aiken, 2003). However, we observe that correlations among our 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 correlation table at the individual level (Table 2.2), which shows that for our 550,000 individual observations, correlations among our independent variables are very low showing that the three individual roles in a firm's network are played by different individuals. 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 a strong firm-level driver of our independent variables and establish their importance above and beyond any effect coming from the the number of inventors in any firm's network. Also, limiting the sample to only large firms made no difference to our results.

[5] We run a number of alternative specifications with various estimation methods. First, we estimated our models using fixed-effects Poisson with bootstrapped standard errors. Second, we estimated our models using fixed-effects least squares with robust standard errors predicting the logarithm of our count dependent variables. Main results were the same; we report differences, if any, in the results section.

Table 2.2
Descriptive Statistics - Correlation Matrix At the Individual Level

		Mean	S.D.	1	2	3	4
1	Star	0.019	0.136				
2	Integrator - Power	0.039	0.192	0.06			
3	Integrator - Reach	0.041	0.199	0.08	0.27		
4	Connector	0.045	0.206	0.18	-0.01	0.10	
5	Isolate	0.016	0.126	-0.01	-0.03	-0.03	-0.03

Note: N = 550921 individual-level observations

In Table 2.3, we provide descriptive statistics and more details about the four types of individual roles. There are two important observations from this table: first, unique inventors remain in the same role for three to four years on average and they generally play the role in consecutive years. This suggests that we are indeed looking at meaningful outliers; individuals do not stay long in their role and they do so only for consecutive years thus showing significant variance and change in our data. Second, we observe significant and 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 show similar size and density but differ significantly in terms of their reach. Connectors are, in fact, bringing different components together, especially when compared to integrators. Connectors are also the most productive among our individual roles and isolates are the least productive. This is additional evidence for the clear distinction between the types of individual roles.

Tables 2.4-2.5 (in the Appendix) depict the regression results for the quantity and quality of inventive output. In both tables, we follow a similar structure in the presentation of results. Model 1 includes only control variables. Models 2-5 include each individual role separately. Model 6 shows the results when we include all individual roles together. Both tables and all models show a stable pattern of results. Integrators-reach are positively and significantly associated with firm-level patent counts ($p<0.01$, Table 4 - Models 3 and 6) and citations ($p<0.01$, Table 5 – Models 3 and 6), while integrators-power have insignificant effects on both. This suggests support for our Hypothesis 1 with a caveat: although size and density of the ego-network are important, the only type of integrators that affects quantity and quality of firm-level inventive output is the type of individuals that combine size and density with reach. Connectors are positively and significantly associated with firm-level patent counts ($p<0.01$, Table 4 -Models 4 and 6) and citations ($p<0.01$, Table 5 – Models 4 and 6), thus providing strong support for our Hypothesis 2. Isolates have an insignificant effect on firm-level patent counts and a weak positive effect on citations ($p<0.1$, Table 5 – Model 6), thus providing some evidence for the positive effect of isolates only on the quality of inventive output.[6]

Table 2.3
Descriptive Statistics - Individual Roles - Mean Values

	Integrator - Power	Integrator - Reach	Connector	Isolate
Observations	21232	22845	24525	8895
Ties	13.60	12.27	11.73	0.00
Ego-network density	65.76	72.54	32.57	0.00
No. of components	1.14	1.19	2.10	0.00
2-step reach	17.63	36.26	11.84	0.00
Nbroker	0.17	0.14	0.34	0.00
No. of patents	5.70	5.13	8.25	2.81
Unique individuals	6012	5203	6537	2627
Average years in role	3.53	4.39	3.75	3.39
Percent consecutive years	91.11%	94.71%	90.03%	98.47%

[6] We also used the number of claims as an alternative measure of the quality of a firm's inventive output. Isolates are positively and significantly associated with claims, thus providing additional and stronger evidence for their effect on the quality of output. The effects of the other three individual roles on claims are exactly the same as in counts and citations.

Table 2.6 (in the Appendix) depicts the results of some alternative model specifications. Models 1-3 predict the effects of individual roles on patent counts and Models 4-6 the same effects on citations. In Models 1 and 4 we explore the potential for non-linear effects of the roles on patents and citations, respectively. Results suggest that the positive effects of integrators-reach and connectors on patent counts and citations are not non-linear. There is some evidence of an inverted-U relationship between integrators-power and citations ($p<0.05$, Model 4). In Models 2 and 5, we include the dependent variable (counts in Model 2 and citations in Model 5) lagged as a right hand side variable to explore for the effects of roles on annual change in our dependent variables and show the robustness of our findings under these specifications. Our results remain unchanged. In Models 3 and 6, we add a control for R&D expenses; the number of observations declines considerably in these two models as we don't have data about R&D expenses from all firm-years in our sample; our results again remain unchanged.[7]

In Table 2.7 (in the Appendix), we report our results predicting the productivity of a firm's inventive output. Model 1 includes only control variables. Models 2-5 include each individual role separately. Model 6 shows the results when we include all individual roles together. Isolates are positively and significantly associated with inventive productivity ($p<0.01$, Models 5-6), thus providing strong support for our Hypothesis 3. Integrators-power are negatively and significantly associated with inventive productivity

[7] We also used alternative estimation methods for our models. The results with Poisson estimation were exactly the same for all roles and patent counts. They were exactly the same for three of four roles and citations; the only difference was that the coefficients of integrators-reach were positive but insignificant. They were the same for all roles and claims (connectors were positive and insignificant for one of the specifications). The results with least squares estimation and the log of dependent variables were the same for all four individual roles and all three dependent variables, with the exception of the prevalence of inverted-U relationships instead of linear effects. Nevertheless, the negative binomial estimation method is by far the most appropriate fit with our data; therefore, results from other estimations should be carefully interpreted as simply robustness checks.

($p<0.01$, Models 2 and 6), thus providing strong support for our Hypothesis 4. Connectors are not significant drivers of productivity and integrators-reach are negative and significant predictors only when included separately ($p<0.05$, Model 3).

We also report some interesting results from our control variables. The size of the network is positively and significantly associated with quantity and quality of inventive output and negatively and significantly associated with productivity under all specifications and estimation methods. Interestingly, star inventors are negatively associated with the quantity and quality of inventive output. On the other hand, stars are strong positive drivers of productivity. This is an interesting pattern of results about the role of stars on different dimensions of inventive output. However, the results for stars should be interpreted with caution as we define them as star inventors and not as star scientists as existing literature does.

2.5. Discussion

In this study, we extended current research on the role of individuals as origins of organizational innovative outcomes. In particular, we developed a theory on some of invention's structural individual microfoundations. We moved beyond existing research focus on individual productivity which may have obscured the importance of other critical individual skills for successful invention. Invention is increasingly a team-based endeavor (Wuchty et al., 2007) and is often an outcome of knowledge recombination from existing knowledge stocks (Fleming, 2001). Therefore, there is a set of collaborative and social skills that individuals need to possess to facilitate the invention process. To identify these individual roles more likely to drive inventive output, we applied social network- and knowledge-based thinking to intraorganizational collaborative networks emerging through co-patenting individual efforts. Conceptualizing invention as a process of recombinant search, we argued for the critical role of three individual types: integrators, connectors, and isolates.

Integrators are the individuals who have a large dense 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 used the term 'relational stars' to describe integrators and connectors in order to emphasize the social nature of their individual capacities and depart from productivity stars. Isolates are individuals who remain unconnected from the collaborative network; they are independent producers of knowledge. Isolates are important because they can infuse the knowledge base with diversity as their knowledge remains unaffected by the organization's knowledge directions and these benefits come at the lowest possible cost for the organization.

There are three interesting aspects of our theory. First, we introduced the notion of relational stars and explained why, apart from simple individual productivity, individual relational capacities are at least as important for the effective implementation of the invention process. We described how certain individuals, who are outliers in terms of their collaborative behavior, end up occupying such network positions in their firm's network that make them consequential for the inventive performance of the firm as a whole. Second, we explained why and how the presence of relational stars translates into firm-level outcomes beyond individual-level outcomes. Third, we argued that different individual roles have heterogeneous effects on different dimensions of their firm's output. While relational stars should drive the overall quantity and quality of output, isolates should be the ones positively affecting productivity.

The results provided ample support to our theory. Relational stars were positively associated with both quantity and quality of inventive output. Interestingly, only one type of integrators – the ones combining size, density, and reach – was a positive driver of quantity and quality. We also found some weaker evidence about the positive impact of isolates on those inventive outcomes. On the other hand, when it came to productivity of inventive output, relational stars had insignificant effects – which even turned negative in the case of some integrators. It was isolates and star inventors that were strongly positively associated with the productivity of their firm's inventive output. Interestingly, we came up with these results based on a large-scale comprehensive longitudinal study, which allowed us to show the effects of individual roles above and beyond firm-level variables and actions that we already know affect invention.

Our arguments and findings have several significant theoretical implications. We offer two important contributions to 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 invention, certain individuals exhibit patterns of collaborative behavior which make them really valuable as sources of organizational capabilities to generate more and high quality inventions. With our findings, we echo early research on the promise of the industrial research laboratory to bring together "intuitive minds", "experimenters", and "observers" to result in successful inventions (Beer, 1959: 71), roles which arguably correspond to isolates, connectors, and integrators, respectively. More importantly, these individuals affected inventive outcomes without being necessarily extremely productive; instead, it was their collaborative behavior which provided them with opportunities for firm-level impact. Second, we moved beyond the one-size-fits-all conceptualization of important individuals on firm-level outcomes. We explained why and showed that different types of individuals affect different dimensions of their firm's knowledge outcomes.

Second, our study has important implications for research on intrafirm knowledge networks. Prior research has been able to document that position of individuals in these networks matters for their own individual outcomes and that the structure of the network affects network outcomes. Here, we showed how micro-level network phenomena can translate into macro-level network outcomes and how the presence of individual nodes in a network (relational stars) affects network level outcomes (inventive output of the organization). Two recent reviews in the topic suggested that such efforts are necessary (Brass et al. 2004; Ibarra et al., 2005). To do that, 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 every competing organization's network, we explained how their presence translates into firm-level outcomes, and we extended current thinking about the importance of centrality and brokering behavior.

As every study, this one has its own limitations. We relied on co-patenting to build internal knowledge networks and instead of tracking knowledge flows, we assumed their presence in the co-patenting ties. However, this is likely a valid assumption; there is research supporting our claim that co-patenting involves significant knowledge flows (Singh, 2005). Moreover, there is a possibility that our relational stars may not be active in knowledge 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, 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 indifferent to the origins of relational stars. Individuals may become relational stars because of their own ability (Lee, 2010), interfirm mobility, or alternatively, because of firm-specific structures or incentives. We make an assumption here that the three types have similar effects on outcomes. This may very well be a quite valid assumption; however, with our existing empirical design we are unable to disentangle them. This observation that relational stars can be an organizational product as well opens the door for interesting future research extensions. What can firms do to identify or internally develop them? Which are the origins of relational stars? These are individuals who had both the ability and opportunity to become relational stars. Therefore, future research can follow the 'opportunity' path and identify contexts which 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).

We conclude with our study's implications for managerial practice. 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 (Almeida & Kogut, 1999), and they are pretty visible to the market and therefore more likely to be hired away (Gardner, 2005). In addition, except for their ex ante identification, there is no other straightforward way for managers to internally build them. On the other hand, relational stars 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. Individuals whose performance depends on interactions with others cannot transfer easily their performance to other organizations (Groysberg et al., 2008). Individual collaboration generates spillovers (Oettl, 2011) 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. More importantly, managers can design practices, incentives, structures, or reward schemes to internally develop relational stars. They can do that by incentivizing the right type of collaboration among employees and develop internally the skills of their intellectual capital resources which may remain untapped.

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CHAPTER 2 APPENDIX

Table 2.1

Descriptive Statistics and Bivariate Correlation Matrix

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Patent counts	46.73	67.70																		
2	Patent citations	323.26	476.90	0.88																	
3	Patent claims	523.10	767.36	0.94	0.89																
4	Patent productivity	0.53	0.26	0.33	0.36	0.36															
5	Firm merged	0.12	0.33	0.18	0.14	0.15	0.00														
6	European firm	0.30	0.46	0.19	0.07	0.14	0.02	0.08													
7	US firm	0.34	0.47	0.17	0.31	0.23	0.54	0.16	-0.47												
8	Pharma firm	0.46	0.50	-0.24	-0.23	-0.24	-0.07	0.02	0.03	-0.06											
9	Alliances	1.64	3.47	0.19	0.14	0.16	-0.03	0.27	0.02	0.13	0.06										
10	Acquisitions	0.25	1.04	0.16	0.12	0.14	0.01	0.30	0.04	0.12	0.09	0.33									
11	Biotech patents	18.30	26.66	0.68	0.57	0.62	0.21	0.36	0.14	0.18	0.05	0.41	0.35								
12	Biotech focus	0.42	0.45	-0.15	-0.17	-0.15	-0.18	0.16	0.09	-0.14	0.36	0.15	0.13	0.17							
13	Network size	237.38	292.67	0.87	0.74	0.79	0.08	0.26	0.20	0.06	-0.28	0.25	0.19	0.61	-0.13						
14	Inventors annual	82.92	109.93	0.94	0.79	0.86	0.11	0.22	0.20	0.05	-0.24	0.25	0.18	0.67	-0.11	0.94					
15	Stars	4.26	11.01	0.71	0.51	0.57	0.11	0.22	0.19	0.03	-0.12	0.26	0.18	0.60	-0.05	0.76	0.78				
16	Integrators - Power	8.67	19.37	0.41	0.25	0.27	-0.19	0.14	0.12	-0.14	-0.03	0.18	0.12	0.42	0.06	0.56	0.58	0.69			
17	Integrators - Reach	9.31	23.93	-0.14	-0.17	-0.15	-0.28	-0.05	-0.05	-0.17	0.14	0.00	-0.04	-0.03	0.20	-0.08	-0.06	0.03	0.43		
18	Connectors	10.04	18.68	0.56	0.37	0.39	0.00	0.23	0.14	0.00	-0.10	0.28	0.16	0.53	-0.01	0.65	0.67	0.83	0.65	0.03	
19	Isolates	3.64	8.27	0.53	0.62	0.57	0.40	0.06	0.00	0.33	-0.21	0.00	0.02	0.18	-0.16	0.43	0.37	0.12	-0.06	-0.16	-0.02

Note: N = 2371 firm-year observations

Table 2.4

Results of Fixed-Effects Negative Binomial Regression Predicting Firm-Level Patent Counts (w/ Bootstrapped Errors) [a,b]

Variables	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
Constant	2.117	**	(0.373)	2.137	**	(0.341)	2.155	**	(0.334)	2.147	**	(0.356)	2.167	**	(0.378)	2.201	**	(0.333)
Year Effects	Incl.	**		Incl.	**		Incl.	**		Incl.	**		Incl.	**		Incl.	**	
Merged	-0.127		(0.088)	-0.125	†	(0.073)	-0.101		(0.079)	-0.111		(0.078)	-0.087		(0.079)	-0.053		(0.070)
EU	-0.708		(0.490)	-0.707	†	(0.371)	-0.759	†	(0.413)	-0.627		(0.404)	-0.757	†	(0.392)	-0.722	*	(0.366)
US	-0.022		(0.433)	-0.044		(0.329)	-0.028		(0.351)	-0.021		(0.362)	-0.121		(0.381)	-0.095		(0.317)
Pharma	-0.027		(0.275)	-0.053		(0.277)	-0.007		(0.223)	-0.106		(0.259)	0.003		(0.261)	-0.014		(0.256)
Alliances	-0.002		(0.004)	-0.002		(0.004)	-0.002		(0.004)	-0.003		(0.004)	-0.002		(0.005)	-0.003		(0.004)
Acquisitions	-0.023		(0.016)	-0.027	*	(0.013)	-0.021		(0.013)	-0.030		(0.020)	-0.029	†	(0.016)	-0.028	†	(0.017)
Biotech Patents	0.008	**	(0.002)	0.008	**	(0.001)	0.008	**	(0.002)	0.007	**	(0.001)	0.007	**	(0.002)	0.007	**	(0.002)
Biotech Focus	0.081		(0.066)	0.080		(0.077)	0.073		(0.066)	0.083		(0.067)	0.089	†	(0.053)	0.083		(0.068)
Network Size	0.001	*	(0.000)	0.001	**	(0.000)	0.001	**	(0.000)	0.001	**	(0.000)	0.001	*	(0.000)	0.001	**	(0.000)
Stars	-0.008		(0.008)	-0.009	†	(0.005)	-0.010	†	(0.005)	-0.015	*	(0.007)	-0.007		(0.007)	-0.015	*	(0.006)
Integrators - Power				0.001		(0.002)										-0.001		(0.002)
Integrators- Reach							0.005	**	(0.001)							0.005	**	(0.001)
Connectors										0.007	**	(0.003)				0.007	**	(0.002)
Isolates													0.013		(0.010)	0.012		(0.010)
Wald χ^2	1998.43**			1944.74**			3611.88**			3241.37**			5824.5**			2763.06**		
Obs / Groups	2414/106			2414/106			2414/106			2414/106			2414/106			2414/106		

[a] One-tailed tests for hypothesized effects and two-tailed tests for control variables. Bootstrapped standard errors are in parentheses

[b] †p < .10
*p < .05
**p < .01

Table 2.5

Results of Fixed-Effects Negative Binomial Regression Predicting Firm-Level Patent Citations (w/ Bootstrapped Errors) [a,b]

Variables	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
Constant	0.743	**	(0.178)	0.750	**	(0.172)	0.732	**	(0.194)	0.763	**	(0.194)	0.765	**	(0.165)	0.763	**	(0.180)
Year Effects	Incl.	**		Incl.	**		Incl.	**		Incl.	**		Incl.	**		Incl.	**	
Merged	-0.047		(0.088)	-0.042		(0.096)	-0.021		(0.094)	-0.030		(0.106)	-0.011		(0.099)	0.022		(0.102)
EU	-0.345		(0.274)	-0.336		(0.288)	-0.339	†	(0.189)	-0.305		(0.245)	-0.363		(0.261)	-0.314		(0.264)
US	0.380	†	(0.199)	0.386	*	(0.192)	0.413	†	(0.225)	0.373	†	(0.222)	0.320		(0.201)	0.348		(0.214)
Pharma	-0.379	†	(0.203)	-0.400	*	(0.181)	-0.403	†	(0.224)	-0.395	†	(0.204)	-0.341	†	(0.201)	-0.369	†	(0.201)
Alliances	-0.002		(0.007)	-0.002		(0.007)	-0.002		(0.007)	-0.003		(0.006)	-0.002		(0.006)	-0.004		(0.005)
Acquisitions	-0.006		(0.015)	-0.012		(0.015)	-0.004		(0.013)	-0.014		(0.018)	-0.012		(0.018)	-0.014		(0.017)
Biotech Patents	0.008	**	(0.001)	0.008	**	(0.001)	0.009	**	(0.001)	0.008	**	(0.001)	0.008	**	(0.001)	0.008	**	(0.001)
Biotech Focus	0.143	†	(0.077)	0.142	*	(0.071)	0.137		(0.084)	0.144	*	(0.066)	0.146	*	(0.067)	0.142	*	(0.068)
Network Size	0.001	**	(0.000)	0.001	**	(0.000)	0.001	**	(0.000)	0.001	**	(0.000)	0.001	**	(0.000)	0.001	**	(0.000)
Stars	-0.015	*	(0.007)	-0.017	*	(0.008)	-0.016	†	(0.008)	-0.024	**	(0.007)	-0.013		(0.008)	-0.023	**	(0.006)
Integrators - Power				0.002		(0.003)										-0.001		(0.002)
Integrators- Reach							0.004	**	(0.001)							0.004	**	(0.001)
Connectors										0.010	**	(0.003)				0.010	**	(0.003)
Isolates													0.014		(0.011)	0.012	†	(0.009)
Wald χ^2	1676.56**			4211.54**			2923.4**			5189.79**			1811.97**			3325.13**		
Obs / Groups	2414/106			2414/106			2414/106			2414/106			2414/106			2414/106		

[a] One-tailed tests for hypothesized effects and two-tailed tests for control variables. Bootstrapped standard errors are in parentheses

[b] †p < .10
*p < .05
**p < .01

Table 2.6

Fixed-Effects Negative Binomial Regression Predicting Patent Counts and Citations (w/ Bootstrapped Errors) - Alternative Specifications [a,b]

	Patent Counts						Patent Citations					
Variables	**Model 1**		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**	
Constant	2.543 **	(0.398)	2.281 **	(0.335)	3.549 **	(0.667)	1.063 **	(0.198)	0.829 **	(0.148)	1.172 **	(0.228)
Year Effects	Incl. **		Incl. **		Incl. **		Incl. **		Incl. **		Incl. **	
Merged	-0.066	(0.064)	-0.041	(0.086)	0.074	(0.083)	-0.018	(0.081)	0.033	(0.085)	0.101	(0.112)
EU	-0.760	(0.490)	-0.749 †	(0.389)	-1.793 **	(0.666)	-0.318	(0.246)	-0.301	(0.273)	-0.844 **	(0.278)
US	-0.127	(0.416)	-0.089	(0.303)	-1.136 †	(0.655)	0.338	(0.215)	0.341 †	(0.206)	-0.044	(0.240)
Pharma	-0.016	(0.292)	-0.007	(0.256)	-0.337	(0.278)	-0.359 †	(0.191)	-0.385 *	(0.173)	-0.493 *	(0.197)
Alliances	-0.001	(0.003)	-0.003	(0.004)	-0.003	(0.004)	-0.002	(0.005)	-0.002	(0.005)	-0.003	(0.007)
Acquisitions	-0.033 †	(0.018)	-0.032 *	(0.014)	-0.027	(0.017)	-0.014	(0.017)	-0.013	(0.015)	-0.020	(0.017)
Biotech Patents	0.005 **	(0.001)	0.006 **	(0.001)	0.006 **	(0.002)	0.006 **	(0.001)	0.007 **	(0.001)	0.007 **	(0.001)
Biotech Focus	0.094 †	(0.054)	0.088	(0.069)	0.055	(0.060)	0.150 *	(0.073)	0.149 *	(0.071)	0.122	(0.099)
Lagged DV			0.003 **	(0.001)					0.000 **	(0.000)		
R&D Expenses					0.000	(0.000)					0.000	(0.000)
Network Size	0.001 **	(0.000)	0.001 †	(0.000)	0.001 **	(0.000)	0.001 **	(0.000)	0.001 **	(0.000)	0.001 **	(0.000)
Stars	-0.077	(0.108)	-0.016 **	(0.005)	-0.014 †	(0.008)	-0.213 *	(0.095)	-0.020 **	(0.005)	-0.021 **	(0.008)
Stars Sq	-0.003	(0.036)					0.005	(0.020)				
Integrators - Power	0.068	(0.068)	0.000	(0.001)	-0.002	(0.002)	0.163 *	(0.088)	0.000	(0.002)	-0.001	(0.002)
Integrators - Power Sq	-0.013	(0.013)					-0.026 *	(0.015)				
Integrators - Reach	0.135 **	(0.055)	0.005 **	(0.001)	0.004 **	(0.002)	0.117 *	(0.067)	0.004 **	(0.001)	0.003 †	(0.002)
Integrators - Reach Sq	-0.009	(0.011)					-0.015	(0.018)				
Connectors	0.186 *	(0.090)	0.007 **	(0.003)	0.007 **	(0.003)	0.228 **	(0.085)	0.009 **	(0.003)	0.011 **	(0.003)
Connectors Sq	-0.013	(0.042)					-0.013	(0.041)				
Isolates	0.331 **	(0.072)	0.010	(0.010)	0.008	(0.010)	0.354 **	(0.095)	0.010	(0.009)	0.011	(0.010)
Isolates Sq	-0.021	(0.018)					-0.022	(0.029)				
Wald χ^2	14847.29**		6694.13**		11240.24**		13985.66**		8498.34**		3937.17**	
Obs / Groups	2414/106		2414/106		1570/103		2414/106		2414/106		1570/103	

[a] One-tailed tests for hypothesized effects and two-tailed tests for control variables. Bootstrapped standard errors are in parentheses

[b] †p < .10
*p < .05
**p < .01

Table 2.7

Results of Fixed-Effects Least Squares Regression Predicting Firm-Level Patent Productivity (w/ Robust Errors) [a,b]

Variables	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
Constant	0.712	**	(0.029)	0.710	**	(0.029)	0.732	**	(0.194)	0.712	**	(0.029)	0.692	**	(0.030)	0.691	**	(0.030)
Year Effects	Incl.	**		Incl.	**		Incl.	**		Incl.	**		Incl.	**		Incl.	**	
Merged	-0.065	*	(0.026)	-0.066	*	(0.026)	-0.067	*	(0.026)	-0.065	*	(0.026)	-0.053	*	(0.026)	-0.055	*	(0.025)
EU	(drop)			(drop)			(drop)			(drop)			(drop)			(drop)		
US	(drop)			(drop)			(drop)			(drop)			(drop)			(drop)		
Pharma	(drop)			(drop)			(drop)			(drop)			(drop)			(drop)		
Alliances	-0.004		(0.002)	-0.003		(0.002)	-0.004		(0.002)	-0.004		(0.002)	-0.004		(0.002)	-0.004		(0.002)
Acquisitions	-0.008	†	(0.004)	-0.006		(0.004)	-0.008	†	(0.004)	-0.008	†	(0.004)	-0.009	*	(0.004)	-0.008	†	(0.004)
Biotech Patents	0.002	**	(0.000)	0.002	**	(0.000)	0.002	**	(0.000)	0.002	**	(0.000)	0.002	**	(0.000)	0.002	**	(0.000)
Biotech Focus	-0.019		(0.023)	-0.018		(0.022)	-0.018		(0.023)	-0.019		(0.023)	-0.019		(0.021)	-0.018		(0.021)
Network Size	0.000	**	(0.000)	0.000	**	(0.000)	0.000	**	(0.000)	0.000	**	(0.000)	0.000	**	(0.000)	0.000	**	(0.000)
Stars	0.003	**	(0.001)	0.005	**	(0.001)	0.004	**	(0.001)	0.003	**	(0.001)	0.003	**	(0.001)	0.005	**	(0.001)
Integrators - Power				-0.002	**	(0.000)										-0.002	**	(0.000)
Integrators- Reach							-0.001	*	(0.000)							0.000		(0.000)
Connectors										0.000		(0.001)				0.000		(0.001)
Isolates													0.007	**	(0.003)	0.007	**	(0.002)
F	8.64**			10.93**			8.6**			8.4**			8.61**			9.77**		
R^2	0.13			0.20			0.15			0.13			0.28			0.35		
Obs / Groups	2344/106			2344/106			2344/106			2344/106			2344/106			2344/106		

[a] One-tailed tests for hypothesized effects and two-tailed tests for control variables. Robust standard errors are in parentheses

[b] †$p < .10$
*$p < .05$
**$p < .01$

CHAPTER 3

COORDINATING INTRAFIRM KNOWLEDGE NETWORKS FOR EXPLORATION, EXPLOITATION, AND AMBIDEXTERITY: A LOOK AT THE MICROFOUNDATIONS OF LEARNING

3.1. Introduction

One of the most enduring themes in innovation research is the critical role of organizational learning as an antecedent of organizational innovative output. More specifically, we know that if incumbent firms in high tech industries, in particular, want to remain innovative they have to continuously renew their knowledge base. Such renewal includes two components: discontinuous strategic transformations and incremental improvements of the knowledge base (Agarwal and Helfat, 2009). Scholars argue that incumbents' renewal requires the development of capabilities (Kogut and Zander, 1992), competences (Henderson and Cockburn, 1994), or dynamic capabilities (Teece et al., 1997) in order to initiate or respond to frequent technological and market changes. In addition, we know that individuals, as the realistic locus of knowledge (Felin and Hesterly, 2007), are probably the meaningful microfoundations of the necessary capabilities (Felin and Foss, 2005). However, much less is known with respect to the importance of specific individual roles and micro-level coordinating mechanisms for the successful implementation of the two components of strategic renewal. In what follows, I make an effort to answer two related questions: first, who are the individual types that drive successful implementation of the two components of renewal? Second, what is the best way to coordinate individuals across the two seemingly inconsistent components to maximize the capacity of the organization to effectively implement both components simultaneously?

Technological change can take various forms and pose mixed challenges on incumbents. Scientific advances disrupt incumbents' existing technological competences (Tushman and Anderson, 1986), novel recombinations alter the technological paradigm (Anderson and Tushman, 1990), and ever present slight changes in the existing technological trajectory require 'normal' technical progress (Dosi, 1982). To update their knowledge base, incumbents engage in exploratory learning, which stimulates development of radically new knowledge, or exploitative learning, which emphasizes incremental refinement of existing knowledge stocks (March, 1991). Individuals are the realistic agents of such learning. Existing research indicates that incumbents' learning activities benefit from investments in individual expertise and productivity (Furukawa and Goto, 2006; Lacetera et al., 2004; Rothaermel and Hess, 2007; Zucker and Darby, 1997). However, individual productivity as an all-encompassing concept is quite fuzzy. Without digging into its components, we fail to understand several important aspects: how exactly did this productivity occur? Did the individual produce new knowledge by recombining proximate knowledge pieces, distant knowledge stocks, or by independently producing new knowledge?

The exact process through which each individual reached a certain productivity level is critical in order to understand the importance of different individuals for the different types of learning. Evidence suggests that innovation is a communal team-based endeavor (Wuchty et al., 2007). Incumbents design structures, processes, and procedures to stimulate knowledge exchange (Tsai and Ghoshal, 1998), recombination (Henderson and Clark, 1990), reconfiguration (Henderson and Cockburn, 1994), diffusion (Fleming, 2002), and search (Gavetti and Levinthal, 2000). My main argument is that at the firm level exploratory learning occurs by expanding knowledge breadth and exploitative learning occurs by increasing knowledge depth. Consequently, individuals who recombine knowledge across local and distant knowledge clusters facilitate exploration and individuals who specialize and independently generate knowledge facilitate exploitation. Therefore, although all individual types may be productive, the exact way through which they are productive matters for organizational-level learning outcomes. To identify the corresponding individual types, I look at intrafirm knowledge networks emerging through individual collaboration for knowledge co-creation. I find that individuals with extreme collaborative behavior, either locally or distantly, drive exploratory output and productive but isolated individuals drive exploitative output. As a result, I identify the different role-sets of individuals required to support the different types of learning, and I contribute to an area where theory and evidence is scarce (Gupta et al., 2006).

In addition, I make an effort to understand what is the best way to organize individuals across activities to maximize the capacity of the organization to do both, effectively. O'Reilly and Tushman (2007) argue that exploratory and exploitative activities require fundamentally different mindsets, routines, skills, and organizational designs. For this reason, scholars suggest that successful incumbents are those able to simultaneously satisfy adaptability and alignment objectives (Gibson and Birkinshaw, 2004) and that the ability of an organization to achieve that critical balance is, in fact, a dynamic capability described by the concept of organizational ambidexterity (O'Reilly and Tushman, 2007). For the same reason, received wisdom suggests that organizations must separate these activities structurally (Tushman and O'Reilly, 1996), temporally (Brown and Eisenhardt, 1997), contextually (Gibson and Birkinshaw, 2004), or tactically (Adler et al., 1999). A major challenge in the process is the need to motivate production of radically new knowledge and integrate it into the incumbent's existing knowledge base (Raisch et al., 2009). As a result, while separation solves the problem of fundamentally different mindsets, it creates the problem of effective selection and transfer of knowledge from one activity to the other. In this paper, I challenge conventional wisdom and I explain why complete separation may actually hamper the pursuit of ambidexterity. In addition, I explain why separation may not be necessary if one looks at the individual level of analysis. I find that an organization's ambidextrous output relies on individuals who are good at both exploration and exploitation and that it is a positive function of the level of connectedness between individuals exploring for new knowledge and individuals exploiting existing knowledge. As a result, I identify the role-set of individuals and the micro-level coordinating mechanisms which can facilitate successful implementation of the selection and transfer of discontinuous knowledge into the firm's knowledge base, a micro-level analysis of the individual role in ambidexterity which has been overlooked (Raisch and Birkinshaw, 2008).

Overall, the phenomenon of interest is the strategic renewal of knowledge bases for incumbents operating in dynamic environments, defined as the demand for incumbents to infuse their knowledge base with radically new knowledge while incrementally improving their existing knowledge stocks. I view incumbent learning as the mean to this end, with learning involving an evolutionary process of knowledge recombination, selection, transfer, and application. These processes map well to the broader categories of exploratory, transformative, and exploitative learning. Finally, I rely on insights from network and knowledge-based theory to link individual role-sets and firm-level coordinating arrangements with the different stages of the learning process. I make an effort to answer a number of related questions: which individual roles are necessary for radical learning and which roles are important for incremental learning? More importantly, which individual-level coordination mechanisms are required to effectively link knowledge coming from exploration with existing internal workings and facilitate the organization's pursuit of ambidexterity in times of technological change? Which of these coordinating mechanisms are more effective than others? In what follows, I provide background on the variables of interest from prior research, highlight gaps in our understanding, present the theoretical model of strategic renewal, and identify types of individuals critical for each stage of the learning process.

3.2. Background and Gaps: Individuals, Networks, and Learning

Technological paradigms are affected by advances that were exogenously-induced, endogenously accumulated (Dosi, 1988) or even randomly emerged (Rosenberg, 1990). Incumbents' survival depends on renewal of their existing knowledge base with radically new knowledge (March, 1991). Here, I take stock of our current knowledge about the role of individuals, internal networks, and learning as drivers of this technological renewal process.

Scholars in economics (Cohen, 1995) and management (Ahuja et al., 2008) are increasingly shifting attention to routines and capabilities as drivers of technological trajectory renewal. Theoretical support of individuals as the realistic locus of knowledge channeled some research towards the role of human capital in incumbent innovation and renewal (Felin and Hesterly, 2007). Significant evidence supports the view that productive individuals with the capacity to generate scientific knowledge facilitate incumbent adaptation. 'Star scientists' are instrumental for knowledge sensing (Lacetera et al., 2004), knowledge in-flows (Furukawa and Goto, 2006), change in technological base (Zucker and Darby, 1997), knowledge capture (Zucker et al., 2002), and adaptation to radical discontinuities (Rothaermel and Hess, 2007). However, while individual intuition is often the trigger of strategic renewal (Crossan et al., 1999), individual creativity has an apparent social side and is affected by the working environment (Amabile et al. 1996; Perry-Smith and Shalley, 2003). Organizations have an advantage because they can internally develop intellectual capital based on social interactions among their members (Nahapiet and Ghoshal, 1998). Early research on the emergence of the industrial research laboratory suggested that its advantage was that "it could take several men, 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). Therefore, although we have a deep understanding of the benefits provided by individual knowledge productivity, there is a set of social and collaborative individual skills that have not received the necessary research attention.

With respect to the role of internal networks in strategic renewal, scholars have recognized that the structure of internal knowledge networks significantly affects innovation outcomes. Centralized R&D structures generate more impactful innovations

(Argyres and Silverman, 2004) while more relaxed structures facilitate improvisation (Brown and Eisenhardt, 1997). Network heterogeneity enhances learning capabilities (Reagans and Zuckerman, 2001), while cohesive and extensive networks affect motivations and abilities for knowledge sharing (Reagans and McEvily, 2003). Efficient networks diffuse information and perform better in the short run but worse in the long-run (Lazer and Friedman, 2007). In addition, social capital developed through interactions affects product innovations (Tsai and Ghoshal, 1998), and collective invention relies on networks combining dense interactions with bridging ties (Cowan and Jonard, 2003). Network structures seem to influence outcomes as broad as knowledge management, innovation, and performance (Borgatti and Foster, 2003). However, although there is evidence that knowledge of central actors shapes the firms' technological capabilities (Nerkar and Paruchuri, 2005), research on the role of specific individuals in the internal networks is scarce. In addition, as the authors of a recent review conclude, another question which remains largely unanswered is "at different stages of the creative or innovative process, are different types of people or skills required…" (Gupta et al., 2006: 703).

With respect to the role of learning in strategic renewal, research suggests that incumbents should structurally separate units responsible for exploration from units responsible for exploitation to address conflicting incentives and demands (Benner and Tushman, 2003; Gilbert, 2005). Alternatively, incumbents can temporally separate units responsible for these inconsistent processes (Brown and Eisenhardt, 1997). Incumbents may also design a context that allows individuals to independently decide whether they will address adaptability or alignment concerns (Gibson and Birkinshaw, 2004) or combine these integrated contexts with tactical separation across time or units (Adler et al., 1999). Research at the individual level focuses on the responsibilities of senior or middle managers to maintain links between different units or design the context for the co-occurrence of continuity and change (Andriopoulos and Lewis, 2009; Taylor and Helfat, 2009). However, there still exists a significant gap with respect to the role of individuals other than managers in implementing those structures and the multi-level processes through which individuals and micro-level coordinating mechanisms may specifically affect ambidexterity at the organizational level (Raisch et al., 2009).

In this article, I propose a model of strategic renewal for incumbents operating in dynamic environments to address these three gaps. First, I separate the renewal process into its components in terms of fundamental knowledge processes: knowledge recombination, selection, transfer, and application. Second, I apply insights from network theory in internal knowledge networks to identify those individuals who based on ideal combinations of ability, motivation, and opportunity end up occupying network positions which make them more effective than others to implement the fundamental knowledge processes. I refer to them as relational stars to emphasize the social and collaborative component of their skills and thus extend current thinking on the importance of 'star scientists'. More importantly, I address existing gaps by identifying certain individual roles as more important than others in driving exploration, exploitation, and ambidexterity.

3.3. Relational Stars and Strategic Renewal

Before proceeding with hypotheses development about the role of individuals in firm-level learning outcomes, I describe here the backbone of the conceptual model at the firm level of analysis and I define some critical constructs. Imagine an incumbent's internal environment. Individuals collaborate to build on the organization's knowledge base and in the process, they form an extensive internal knowledge network. Nodes in this network are individuals participating in the knowledge co-production process (i.e. scientists, engineers, etc.). Ties reflect instances of direct collaboration with the purpose of knowledge co-creation. They can be viewed as strong ties (Hansen, 1999), which are necessary for effective knowledge transfer (Singh, 2005) or recombination (Galunic and Rodan, 1998), and play a dual role as they facilitate both inflows and outflows of knowledge (Borgatti and Foster, 2003).

In this network, individuals are organized around their knowledge domains. Therefore, knowledge clusters emerge representing the various areas in the incumbent's knowledge base. The boundaries of such areas are not determined by geographical, unit, divisional, or functional criteria; rather, they are defined by the nature of knowledge. Interactions within clusters are relatively dense to reflect intense collaboration among individuals working on the same field. Bridging ties across clusters are instances of collaboration across knowledge areas.

Strategic renewal of an incumbent's knowledge base includes the infusion of the knowledge base with radically new knowledge and the incremental improvement of existing knowledge stocks. Therefore, one component is the production of exploratory output, which consists of knowledge stocks radically different from existing ones. Such radically new knowledge may come from either distant or local recombination of existing knowledge stocks achieved by insight or pure luck (Rosenberg, 1990). Recombination may happen within or across knowledge clusters. The emphasis is on the quantity of new combinations as the initiating process is so uncertain that any aspects of quality or value are largely unknown at this point.

In the meantime, within knowledge clusters individuals perform the second component of strategic renewal, that is, the generation of exploitative output. This term refers to the normal technical process of incremental learning which results in incremental improvements of existing knowledge stocks. Again, the focus is on the quantity of such output. The quality or value of those improved knowledge pieces depends on environmental or firm factors that are not captured by my model (Kline and Rosenberg, 1986).

Finally, I highlight here the importance of another critical process for successful renewal, a process that is generally neglected. Knowledge coming from exploratory output must find its way into the incumbent's knowledge base. However, organizations cannot follow every potential knowledge trajectory proposed by exploratory output and the process of integration into the knowledge base is hardly automatic. The linking pins connecting exploratory output with the organization's current knowledge base are the critical processes of knowledge selection and transfer. The former is the selection from the radically new knowledge stocks of the ones that fit with the organization's strategy, assets, culture, or overall goals and the latter is the effective transfer of selected stocks to the clusters for integration with the existing knowledge base.

The outcome of a full strategic renewal cycle is a new knowledge base which includes the selected radically new knowledge stocks produced by exploratory learning and the incrementally new knowledge stocks produced by exploitative learning. If the two processes of selection and transfer are effectively implemented, then radically new knowledge will enter the incumbent's knowledge base, and the incumbent will achieve ambidextrous output defined as the organization's capacity to develop knowledge relying on radical and incremental learning. This output does not contain any performance implications. Instead, the result is a renewed knowledge base and a set of knowledge stocks, of which some were based on knowledge from exploratory learning.

At this point, it is pertinent to highlight some of my theory' underlying assumptions. In my model, exploration and exploitation compete for the same resources and thus are the ends of a continuum (Gupta et al., 2006), a conceptualization which is theoretically more plausible (Lavie et al., 2010). Therefore, in my model the learning activities are neither structurally nor temporally separated. If any separation occurs, it does not occur on the input side. New knowledge pieces are produced by individuals, and these pieces are then ex post characterized as either exploratory or exploitative output. I also assume that individuals have some level of freedom to choose their learning and collaborative behavior (Gibson and Birkinshaw, 2004). Therefore if any separation occurs it is only 'tactical' (Adler et al., 1999). Finally, no assumptions are made with respect to the nature of the knowledge flows (incremental vs. radical) through the ties.

3.3.1. Network Positions as Individual Capacities

Following the process of strong interpersonal collaboration, individuals end up occupying certain positions in the incumbent's internal knowledge network. Network positions indicate a pattern of behavior (i.e. a role). For instance, a node with four ties is an individual having strong collaborative ties with four alters. These ties have three components: structural, cognitive, and relational dimensions (Nahapiet and Ghoshal, 1998). Therefore, a tie indicates that the interacting actors have access to each other's knowledge and may use this information to exchange, diffuse, and combine knowledge stocks. In addition, a tie reflects the underlying presence of somewhat similar knowledge and shared communication codes. Finally, a tie implies interpersonal trust, shared norms, and motivation to share knowledge. As a result, an actor in a certain position has the capacity to utilize all the benefits stemming from the ties to implement the various fundamental knowledge processes that I described earlier. In the hypotheses that follow, I make links between networks positions and outcomes. In reality, the link is between the individual's behavioral pattern, which includes an inherent individual capacity, and the behavior's outcome.

However, it is important to note that these patterns have a certain origin. Actors emerged in their positions because they had the corresponding skills, were appropriately motivated to engage in collaboration, and were provided with the opportunity to do so by the organization's structures, incentives, or strategies. These origins are out of this paper's scope and are briefly discussed in the discussion section. Here, it is important to emphasize that a network position is an organizational product as much as it is a product of individual skills and that actors in network positions have the capacity to alter the organization's knowledge base by utilizing the structural, cognitive, and relational features of their ties.

The logic behind the propositions is the following: for each stage of strategic renewal I identify the associated processes (recombination, selection, etc.) and detect the key actors with the capacity for maximum effectiveness for each process's implementation. Many individuals within the incumbent's network recombine and select knowledge and will not be identified as key actors because here I am interested in the best individuals in every category. This is eventually the same approach as the one taken by scholars studying star scientists. They are looking for the positive effect of the most productive individuals and not just of some productive ones.

3.3.2. Exploratory Output

One source of radically new knowledge is a novel recombination of knowledge stocks achieved by insight or pure luck (Rosenberg, 1990). The overarching idea in this line of research is that individuals are more likely to come up with novel combinations when their networks span structural holes (Burt, 2004) among technologies (Fleming, 2002), disciplines (Henderson and Cockburn, 1994), social structures (Fleming et al., 2007), locations (Singh, 2008), or divisions (Kleinbaum and Tushman, 2007).

Here, I focus on individuals with the ability to span internal knowledge boundaries and connect stocks from diverse internal knowledge bases. I remain indifferent as to whether these combinations require spanning of unit, divisional, or geographic boundaries. Therefore, I define *connectors* as actors who span structural holes (i.e. they are knowledge brokers) in the incumbent's internal network and access the highest share of the network compared to brokers in all other competing organizations' internal networks. With this term, I capture individuals who are the best in collaborating across knowledge domains and utilize a very large share of their organization's knowledge base. While not necessarily productive or highly collaborative, connectors operate as the linking pins between otherwise unconnected and distant knowledge stocks.

They maintain strong collaborations with many internal actors, who are parts of diverse internal knowledge sub-networks, and connect knowledge pieces which would otherwise remain unconnected. In a sense, they work across knowledge silos within their firm's network. Importantly, I define connectors not only as knowledge brokers; their collaborative behavior also allows them to access a large share of their firm's network. In addition, I emphasize here that connectors are outliers in terms of brokering behavior when compared with actors from all competing organizations.

All these attributes are necessary for connectors to have an effect on exploratory output at the firm level. The first mechanism through which connectors can increase their organization's exploratory output is through novel knowledge combinations of diverse knowledge stocks. In other words, their collaborative behavior makes them more likely than other actors to come up with further novel knowledge recombinations. It is important to note that the existence of connectors within incumbents' networks does not necessarily translate into novel recombinations. The ties reflect knowledge co-creation between actors working in incremental and/or radical learning. Assuming though that such actors have an adequate level of freedom to pursue potential avenues for radical learning, connectors are more likely to exhibit entrepreneurial intuition (Crossan and Berdrow, 2003). Therefore, incumbents benefit from connectors because they have the capacity and increased opportunity to come up with a discontinuous novel recombination as they collaborate with actors working in diverse technologies. In addition to brokering behavior, connectors have access to a larger share of the firm's network and therefore, can involve a larger part of the organization's knowledge base to their recombinant efforts.

I shift now attention to explaining why the presence of connectors can more directly translate into firm-level outcomes by making other actors more likely to come up with exploratory new knowledge stocks. Through their behavior, connectors become familiar with who knows what across distant knowledge clusters. As a result, even if they are not equipped to create a new recombination, they can identify promising recombinations that can then be implemented by other actors. Moreover, using knowledge outflows embedded in their ties, connectors can more rapidly diffuse a constantly updating knowledge base to distant knowledge clusters. As a result, connectors develop new knowledge stocks that are then picked up faster by distant teams of collaboration which can simply build on the new knowledge pieces. I emphasize here that all these benefits stemming from connectors are even more pronounced for the outliers in the brokerage-share distribution. This is because every additional tie for any single individual results in an exponential increase in the number of future possible recombinations and in the share of the knowledge network that is informed about the updated knowledge base. For all these reasons,

Hypothesis 1. Ceteris paribus, an incumbent's exploratory output is a positive function of the number of connectors in its network.

A second source of radically new knowledge is through local recombination of knowledge achieved by individuals who have an extraordinarily high number of collaborations and therefore, are able to identify promising novel knowledge combinations that result in knowledge stocks that are radically different from existing ones. I refer to them as *integrators* and define them as the individuals with the highest number of direct ties in their firm's any single knowledge sub-network compared with the ties of their counterparts in the industry's other incumbent firms. Integrators can drive exploratory output not because of novel recombinations across knowledge silos as connectors do, but because of novel recombinations stemming from the fact that they have a very large number of collaborative ties. While connectors affected exploratory output using the type of their collaborative behavior (across knowledge clusters), integrators have a similar effect driven by the extent (ego-network size) of their collaborative behavior. Integrators often exist within a single knowledge area and maintain strong collaborations with actors in that same area, actors who are often connected with each other. Normally, integrators occupy a central position in their firm's network. Although we have extensive evidence for the link between an individual's central position and that individual's performance outcomes, we have a limited understanding of the role of such individuals for network-level outcomes. Similarly to connectors, integrators can affect their firm's exploratory output in three different ways.

First, integrators through knowledge inflows have the capacity to observe a large number of other actors, understand 'who knows what' (Borgatti and Cross, 2003), and follow the most promising local recombinations. Therefore, they are better equipped to identify novel recombinations themselves. Second, through knowledge outflows they have the capacity to effectuate diffusion of the updated knowledge base and initiate further cycles of knowledge exploration by a large number of immediate peers. Third, they can simply point to potential recombinations that can be implemented by others because of their extensive knowledge of different knowledge sources. Again, it is important to underline that integrators are defined as outliers when compared with actors across competing organizations. Outliers have an advantage in this respect because every additional tie has an exponential effect on the number of potential recombinations. For all these reasons, I hypothesize that,

Hypothesis 2. Ceteris paribus, an incumbent's exploratory output is a positive function of the number of integrators in its network.

It is useful to clarify here that the two types of relational stars (connectors and integrators) are not simply proxies for firm-level network structures. Essentially, the difference is between comparing means of a distribution and comparing variances. While firm-level structure variables capture the network's average cohesion, individual level positional metrics capture the relevant outliers. For example, it is quite possible that a firm's network is above average in terms of cohesion and connectedness without having a single integrator-outlier. It is also quite possible that two networks of similar connectedness include quite different numbers of outliers. I argue here that capturing the variance of the distribution and therefore, identifying the individuals-outliers is important and necessary to understand the phenomenon-outcome; as I mentioned earlier, these outliers enjoy disproportionate recombinant advantages as every additional tie results in an exponential increase in the number of potential recombinations.

3.3.3. Exploitative Output

Before proceeding with the discussion of how an incumbent utilizes the radically new knowledge coming from exploratory output, I first identify the individual actors important for the execution of the incumbent's normal progress of incremental learning and exploitative output (Dosi, 1988). Incremental learning more likely happens within the various knowledge sub-networks present in an incumbent's internal network. Focused individuals work within knowledge areas to generate improvements for the firm's existing portfolio of knowledge. Exploitation is at opposite end of the learning continuum when compared to exploration. Therefore, the core idea is this: if exploration is driven by individuals with extreme patterns of collaborative behavior and extensive knowledge recombination, then we should expect that exploitation is driven by individuals who exhibit the opposite behavior, that is, individuals who produce new knowledge without sourcing and recombining knowledge from many sources.

The process of incremental learning, especially within knowledge sub-networks, can be viewed as a pursuit for local optima (Gavetti and Levinthal, 2000). Local optima are more likely to be found by individuals concentrated on a narrow set of knowledge resources. Therefore, for exploitative output to occur, certain individuals should specialize in a narrow knowledge area and generate knowledge that expands in depth rather than in breadth. Such actors should remain relatively unconnected from the rest of the knowledge network to avoid overembeddedness and the 'risk' of social capital (Adler and Kwon, 2002). Actors remaining uncoupled from an organization's network have been characterized as "isolates" (Tichy et al., 1979). Some of those individuals manage to be particularly productive despite (or even because of) their focus on a certain knowledge field and their lack of connectedness with the internal knowledge network. Building on this idea, I define here *productive isolates* as the actors who generate knowledge relevant for one or more knowledge clusters while remaining almost unconnected from the actors in those sub-networks. Therefore, to identify actors who should drive exploitation, I look beyond isolation at the individuals who can be productive while isolated. As a result, such individuals can supply incrementally improved new knowledge stocks at a high rate. Productive isolates improve relatively familiar knowledge within certain knowledge areas usually though a process of individual specialization in narrow knowledge fields and without collaborating and recombining knowledge. In addition, such isolates produce knowledge but remain unaffected by the knowledge directions of the knowledge network thus having the capacity to provide it with additional insights and in-depth incrementally improved knowledge. As a result, they become significant drivers of their organization's exploitative output.

Hypothesis 3. Ceteris paribus, an incumbent's exploitative output is a positive function of the number of productive isolates in its network.

3.3.4. Ambidextrous Output

Radically new knowledge should find its way to the existing knowledge base in order to result in the incumbent's effective strategic renewal. The overall process is similar to what has been labeled as transformative learning (Lane et al., 2006) where the main objective is assimilation of valuable external knowledge. The difference is that in my model the radically new knowledge stocks that need to be assimilated may also be internally sourced. In any case, the organization has a certain number of dissimilar knowledge stocks from exploratory output that need to be integrated into its knowledge base. There are two main coordination challenges in the process of linking radically new with existing knowledge. First, the firm must select among the various new knowledge stocks the most promising pieces and the ones that are consistent with the organization's strategic objectives. The incumbent is bounded by limited resource availability and cannot follow every potential trajectory implied by newly acquired knowledge. The selection process is of critical importance for strategic renewal and it is not a task which happens automatically; rather, carefully designed mechanisms are necessary for its implementation (Brown and Eisenhardt, 1997; Fleming, 2002). Knowledge selection is hampered by the limited ability of actors other than the original source of the new knowledge to determine its potential or fit. In addition, successful selection is further obstructed by internal interpretative barriers; ambitious innovators generate new knowledge which is often faced with illegitimacy because of the presence of internal heterogeneous and often inconsistent 'thought worlds' (Dougherty, 1992; Dougherty and Hardy, 1996). Therefore, it is critical that the task of selection is assigned to actors as close as possible to the source of radically new knowledge.

The second challenge is the rapid transfer of selected new knowledge throughout the organization to initiate the combination process which will eventually result in the transformation of the knowledge into innovations. This is not an automatic process either; it is very difficult to effectively transfer knowledge to individuals who are distant from the original point of knowledge entry (Cohen and Levinthal, 1990), mainly because transfer of complex knowledge requires very strong ties (Hansen, 1999). Scientific ideas and technological knowledge have very conflicting selection logics (Gittelman and Kogut, 2003) and novel recombinations appear to be very difficult to diffuse (Fleming et al., 2007). These two characteristics make it even harder to transfer and transform new knowledge into marketable output. Therefore, it is necessary for any new knowledge stock to travel the minimum possible distance within the organization until it is integrated into the existing knowledge base.

It follows from the previous discussion that radically new knowledge stocks from exploratory output should be tested for selection by actors as close as possible to the original source of generated knowledge and that selected knowledge should be then diffused through the shortest path available. Otherwise, lack of full understanding of the new piece of knowledge will undermine both the assessment of its potential for selection and its effective transfer. Therefore, ideally an incumbent should rely on the same individual who produced the knowledge to make a judgment about its potential value and in turn, diffuse it using the shortest path.

Fortunately, individuals have a characteristic that makes them a special resource: individuals are pretty flexible. Unlike other resources that can be deployed only towards one type of activity at a time, individuals may be able to be good at both exploration and exploitation. As a result, structural separation between exploratory and exploitative activities may not be necessary at the individual level of analysis. This is actually possible as I earlier conceptualized the internal environment as one which provides freedom to individuals to make their own decisions between radical and incremental learning. Evidence suggests that such environments exist in real organizations (Adler et al., 1999; Gibson and Birkinshaw, 2004). In addition, that would require individuals with capacities to both generate radically new knowledge and incrementally improve existing knowledge. Extensive evidence suggests that such individuals also exist: there are individuals who contribute to both science and innovation (Gittelman and Kogut, 2003), authors-inventors who bridge the boundaries between the scientific and the technological domain (Breschi and Catalini, 2010), industrial scientists with revealed preference to both publish and patent (Sauermann and Cohen, 2008), and workers contributing to both routine and non-routine tasks (Adler et al., 1999).

Building on this logic, there seem to be two different ‘qualities’ that individuals can possess. The first implies the capacity to generate radically new knowledge towards exploration and the second implies the capacity to incrementally improve knowledge towards exploitative output. Therefore, I define *ambidextrous individuals* as the individuals with the ability to possess both types of ‘qualities’. These individuals can generate radical knowledge, assess its potential and fit with the incumbent’s strategic objectives (they fully understand it as they are the original source), select the relevant knowledge to be integrated into the existing knowledge base, and transfer it both effectively (without loss of information) and rapidly (through the shortest available path). In essence, these individuals participate in both exploration and exploitation. Hence, incumbents possessing such individuals are in the ideal position to achieve unobstructed implementation of the selection – transfer process. Ambidextrous individuals facilitate the incumbent’s efforts to infuse the existing knowledge base with knowledge coming from exploration. Therefore, the outcome is an updated knowledge base consisting of radically new plus existing knowledge stocks, i.e. a more balanced ambidextrous output.

Hypothesis 4. Ceteris paribus, an incumbent’s ambidextrous output is a positive function of the number of individuals in its network who excel at both exploration and exploitation.

Alternatively, effective selection and transfer of generated discontinuous knowledge can also happen with the presence of strong collaborative ties between actors with the ‘quality’ to explore and actors with the ‘quality’ to exploit. Such ties would reflect a level of connectedness between the source of the radical knowledge and the individuals responsible for its rapid attachment to the incumbent's existing knowledge base. Research suggests that links between the unit of radical learning and the unit of its application are critical for the incumbent's effort to align adaptability with efficiency and achieve ambidexterity (Hill and Rothaermel, 2003; Jansen et al., 2009; Raisch et al., 2009). In terms of selection, the process remains largely unaffected compared to the presence of an ambidextrous individual, because it still involves the origins of the discontinuous knowledge in the selection decision. Understanding of the knowledge components and informed selection is likely to take place. However, in terms of transfer effectiveness this approach entails at least one additional step of knowledge transfer. Therefore, some loss of information is expected and the transfer is at least sub-optimal. On the other hand, because of the fact that ambidextrous individuals may be quite rare, we should still expect ties between actors of complementary 'qualities' to strongly benefit the incumbent's selection-transfer process and subsequently result in successful renewal of the knowledge base. When exploration stars work together with exploitation stars, selection and transfer of radically new knowledge into the knowledge refinement process becomes easier and results in a new balanced knowledge base.

Hypothesis 5. Ceteris paribus, an incumbent's ambidextrous output is a positive function of the level of connectedness between actors responsible for exploration and actors responsible for exploitation.

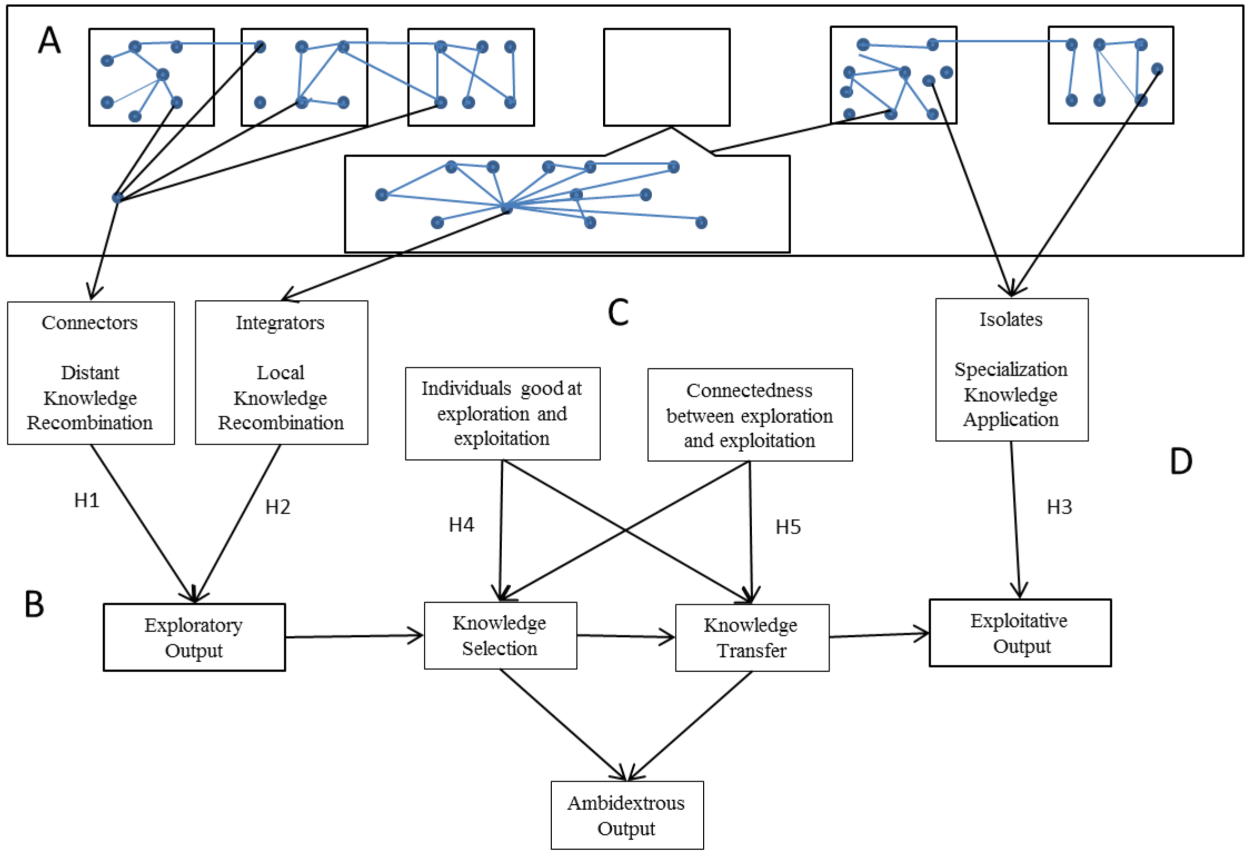

Figure 3.1. The proposed model of strategic renewal.

Figure 1 summarizes my conceptual model. Area A is a random snapshot of an incumbent firm's internal knowledge network for illustration purposes. Area B is a snapshot of the process of generating exploratory output, where connectors and integrators explore through distant and local knowledge recombination. Their position in the internal network reflects their role. Area D is a snapshot of the process of generating exploitative output. Productive isolates within knowledge clusters specialize and remain unconnected thus building on existing knowledge paths and generating exploitative output. Finally, Area C depicts the process of linking knowledge coming from exploratory output into the incumbent's existing knowledge base. If selection and transfer occur effectively, then a balanced ambidextrous output will be positive affected. Effective selection and transfer, in turn, may happen if the incumbent possesses either individuals who excel at both exploration and exploitation or a certain level of connectedness between individuals exploring and individuals exploiting.

3.4. Methods

To test the developed hypotheses, I followed a longitudinal research design in the global pharmaceutical industry. Pharmaceutical firms have followed a number of alternative strategies to remain innovative; they took on alliances, acquisitions, heavy investment in internal research, and in human capital to build or maintain innovative capabilities (Rothaermel and Hess, 2007). Therefore, the pharmaceutical industry is an ideal setting for this paper to explore for the role of relational stars in driving learning above and beyond the mentioned innovation levers. My observation period is from 1974 to 1998. My sample consists of 106 pharmaceutical firms that were active in the production of human in-vivo therapeutics and were founded before 1974. This sample is largely representative of the overall industry as it accounts for the vast majority of global sales of pharmaceutical products. I tracked these 106 firms forward until 1998.

I constructed the key dependent and independent variables relying on patents granted to these firms by the USPTO. The pharmaceutical industry is the industry which relies most on patents when it comes to intellectual property protection compared to all other manufacturing industries (Cohen, Nelson, Walsh, 2000). I used the NBER patent data file (Hall, Jaffe, and Trajtenberg, 2001) to create a full patent portfolio for each one of my firms from 1974 to 1998. Many firms in my sample are dedicated pharmaceutical firms. However, there are many diversified conglomerates that are also active in other industries. I argue that knowledge possessed by inventors in unrelated industries has little to do with my knowledge-based arguments. Therefore, I sampled on the resulting patent portfolio for every firm and I relied on information from technology classes to keep only patents that are assigned to classes with a clear chemistry or biology component and thus are more likely to be related to the technologies underlying human therapeutics.

3.4.1. Dependent Variables

Exploratory Output. The dependent variable for hypotheses H1 and H2 is exploratory output. I made an effort to capture a pharmaceutical firm's exploratory output as accurately as possible by relying on three alternative fine-grained measures, which I report as Exploration_1, Exploration_2, and Exploration_3, respectively in the result tables. First, I capture exploratory output by counting the number of the firm's patents in any single year that have zero self-citations. The idea is that if a new patent does not cite knowledge already held by the organization, it is reasonably new to be characterized as exploration. Second, I make my criteria much stricter and I keep only patents that have zero self-citations but at the same time are at the top of the originality distribution and cite a very small number of other patents in general. The originality measure has been developed by Hall et al. to capture patents that rely on novel combinations of technological fields and are therefore, original. In addition, I employed the number of citations to all other patents (not only self-citations) to argue that patents with only a few citations must be more novel than others. In this way, I also captured knowledge stocks that are new to the industry as a whole and not only to the firm. In the third measure of exploratory output, I relax the citation criterion and define exploratory output as the patents that have zero self-citations and are above average in terms of originality. In this way, I capture knowledge stocks that not only new to the firm but also rely on a novel and original recombination of previously-help knowledge stocks.

Exploitative Output. The dependent variable for hypothesis H3 is exploitative output. Again, to be as accurate as possible, I measured exploitative output using three different measures that are the mirror images of the ones used for exploratory output. Exploitation_1 includes patents that contain only self-citations. In other words, these new knowledge stocks build exclusively on knowledge already held by the organization and therefore, are just incremental improvements of existing knowledge stocks. Exploitation_2 includes patents that contain only self-citations and are at the same time below average in terms of originality. Exploitation_3 captures patents that have some self-citations (not exclusively though) and are again below average in terms of originality. The idea is that when a new patent has a number of self-citations and is not very original, it is reasonable to assume that it constitutes new knowledge that is an incremental improvement over existing knowledge stocks of the firm.

Middle Output. What I eventually do for every firm's patent portfolio, is that I build a continuum from exploration to exploitation and every patent falls at different points of the continuum based on the patent's self-citations, all backward citations, and originality. Then, I characterize as exploratory output the patents that are close to the exploration end of the continuum and as exploitative output the patents that are close to the exploitation end of the continuum. This process essentially leaves a number of patents in the middle;

although I have not hypothesized any effects of relational stars on these middle-level outcomes, I still include them in the analysis to uncover some interesting patterns in the results.

Ambidextrous Output. The dependent variable for hypotheses H4 and H5 is ambidextrous output. I capture this by taking the product between exploratory output and exploitative output. I report the results for ambidextrous output as the product between Exploration_3 and Exploitation_3 as these are the two measures on which I have the highest confidence because they are neither too lenient nor too strict and still include a meaningful number of patents to make the analysis possible. However, results for the other two measures of ambidexterity remain robust.

3.4.2. Intrafirm collaborative networks and independent variables

To identify relational stars, isolates, ambidextrous individuals, and connectedness between exploration and exploitation, I developed intrafirm co-inventing networks for each firm from 1974 to 1998. First, I relied on the NBER database inventor file to find all the individual inventors listed in each firm's patent portfolio. I assigned a unique ID to each individual inventor based on a combination of last name, first name, and middle name. When there was still a conflict, I used information on city and state of residence to separate inventors. Second, I used UCINET 6 to develop intrafirm collaboration networks based on co-patenting events. Nodes of the networks were individual inventors and ties were co-patenting events. Third, I developed the knowledge networks using a five-year rolling window (e.g. 1982-1986 values to 1986, 83-87 values to 87, etc.). The idea there is that knowledge flows occurring through a tie that is older than five years becomes obsolete and therefore, needs to be excluded. As a result, to build networks and define individual positions in a firm's knowledge network in year t, I used information on patenting events that occurred in years t, t-1, t-2, t-3, and t-4. Finally, I analyzed the resulting networks and kept information related to each individual inventor's ego-network (i.e. size, density, brokerage, etc.) to define the individual roles. I also kept information about the number of patents associated with each individual in the same five-year time window. Then, I developed three variables at the inventor level:

Integrator. This is an indicator variable with a value one if the inventor' direct collaborative ties are two standard deviations more than the mean number of direct ties of all inventors of all firms during the same 5-year window **and** the inventor has more than two patents in the same period (to avoid one-time inventors that contribute little to their firm). Therefore, I captured inventors with a great number of alters as collaborators.

Connector. In the theoretical part of the paper, I emphasized that connectors are not only knowledge brokers in terms of spanning many structural holes, but they are also individuals who connect distant clusters of knowledge and therefore have access to a large share of their firm's collaborative network. Therefore, to capture connectors I relied on a combination of two network metrics. First, I selected inventors with more than two patents and more than the mean number of collaborative ties in the firm's network. In this way, I retained only inventors who were not one-time inventors and who had enough ties to have a meaningful connecting impact. Second, I kept inventors whose ego-network density was low (less than one third). Hence, I sampled on inventors who span structural holes; this cutoff point suggests that existing ties among a connector's alters were less than one third of all potential ties among them. Third, among the remaining inventors, I characterized as connectors those whose two-step reach in the network was higher than the mean. Therefore, among the inventors who spanned structural holes, I selected those whose ties allowed them to reach a larger share of the firm's internal collaborative network. The two step reach measure captures the percentage of the network's nodes that a node has access to through its direct and indirect ties. Hence, I combined density with reach in order to identify inventors who span structural holes and at the same time have access to a broader share of the network.

Productive Isolate. This is an indicator variable with a value one if the inventor has patents that are three standard deviations above the mean number of patents of all inventors with fewer than three collaborative ties during the same five-year window. I chose to accept this low level of connections for isolates to support my claim that they have an opportunity to somehow affect the knowledge directions of their organization. However, having two or fewer ties still makes these inventors relatively isolated from their firm's network. At the same time, isolates are the most productive inventors among those with a small number of collaborative ties.

Using these indicator variables at the inventor level, I developed the independent variables at the firm level using counts of *integrators*, *connectors*, and *productive isolates* that each firm possesses in each year from 1974 to 1998 to test hypotheses H1-H3 (again counts from time window 74-78 go to 1978, counts from 75-79 go to 79, etc.).

For hypotheses H4 and H5, I first identified inventors who were really good at exploration and inventors who were really good at exploitation. I characterized as *exploration stars* the top 10% of inventors in terms of exploratory output (their name was associated with exploration patents as measured using the three alternative measures of exploration), and I defined as *exploitation stars* the top 10% of inventors in terms of exploitative output within the same five-year time window among all individuals from all firms. Then, in order to test H4, I captured ambidextrous individuals as the inventors who were at the same time exploration and exploitation stars within the same five-year time window.

For H5, I used two alternative measures. First, I counted the number of ties between exploration and exploitation stars to measure the mere number of pathways from exploration to exploitation through collaboration between the relevant inventors. Second, I divided this count by the number of potential ties (defined as the product of exploration stars times exploitation stars). This resulted in the creation of a *connectedness score* between exploration and exploitation for each firm for each five-year time window, a score which was independent from the mere number of exploration and exploitation stars in its network and captured only how connected are the firm's exploratory and exploitative activities.

3.4.3. Control Variables

I included a series of control variables to control for other factors that have shown to affect a firm's exploratory or exploitative output. First, in every model I included the *dependent variable lagged* as a right hand side variable to make a very conservative test of my hypotheses, address any remaining endogeneity concerns, and possibly control for a specification bias. For hypotheses H1-H2, I controlled for merged firms (merged), EU or US firms, and dedicated pharmaceuticals (pharma). I also controlled for innovative performance (totalpatents), exploration alliances, and acquisitions. I included in my models the number of star inventors (*stars*) that each firm possesses. I followed prior research and defined stars based on their well above average productivity. More importantly, I controlled for the number of inventors in the firm's network (inventors) which is arguably one of the main drivers of the development of integrators, connectors, and isolates. Hence, by controlling for network size I was able to run very conservative tests for my hypotheses as I was able to show that integrators, connectors, and isolates all affect output above and beyond any effect of the overall network size. By including network size which is the number of inventors in every five-year window, I also controlled for the size of each firm and I had a fine-grained measure of research investment in inventive activities. For H3, I controlled for exploitation alliances instead of exploration alliances. In addition to the previously mentioned controls, for H4 and H5 I also included a series of controls that capture every firm's exploratory and exploitative capacity (both stars and output). As a result, I am able to show that my results regarding the effect of micro-level coordinating mechanisms on ambidextrous output hold above and beyond any effect coming from the respective levels and capacities for exploratory and exploitative output independently.

3.4.4. Estimation

Dependent variables (exploratory, exploitative, ambidextrous outputs) are all nonnegative overdispersed count variables. Therefore, I used negative binomial estimation with bootstrapped standard errors. I chose the fixed-effects version to control for remaining unobserved interfirm heterogeneity. Overall, I included the dependent variable lagged as a control, and I constructed the independent variables using 5-year rolling windows. Therefore, along with the rich set of control variables I believe that I did my best to address any remaining endogeneity concerns (Hamilton and Nickerson, 2003).

3.5. Results

Table 3.1 depicts descriptive statistics and bivariate correlations for the variables at the firm level. All directions of correlations appear as expected. Some correlations between individual roles are slightly elevated. Therefore, I also submit the correlation table at the individual level (Table 3.2) to provide further insights on the data. For the 457,859 individual-level observations, correlations among the key independent variables are very close to zero showing that the different individual types capture strongly different individual roles in a firm's network. The only correlation that is elevated is the one between stars and ambidextrous stars (0.51). This is not particularly surprising considering the fact that ambidextrous stars need to have many associated patents assigned to their name in order to have both many exploration and exploitation patents.

Table 3.2 Descriptive Statistics – Correlation Matrix at the Individual Level

Table 2							
Descriptive Statistics - Correlation Matrix At the Individual Level							
		Mean	S.D.	1	2	3	4
1	Star	0.018	0.135				
2	Integrator	0.012	0.107	-0.01			
3	Connector	0.010	0.101	-0.01	-0.01		
4	Isolate	0.009	0.096	0.04	-0.01	-0.01	
5	Ambidextrous Star	0.030	0.170	0.51	0.12	0.07	0.07
Note: N = 457859 individual-level observations							

Table 3.3 Descriptive Statistics – Individual Roles

Table 3					
Descriptive Statistics - Individual Roles - Mean Values					
	Star	Integrators	Connector	Isolate	Ambidextrous Star
Observations	8462	5331	4679	4257	14070
Ties	17.48	22.10	10.60	1.45	13.69
Ego-network density	34.42	39.59	26.23	53.39	39.20
No. of components	1.96	1.53	2.61	1.10	1.86
2-step reach	12.45	26.16	12.53	1.62	10.51
Nbroker	0.33	0.30	0.37	0.16	0.30
No. of patents	23.25	8.18	7.06	8.53	12.30
Unique inventors	1962	1690	1827	1565	3436
Average years in role	4.31	3.27	2.56	2.72	4.09
Percent consecutive years	96.60%	92.10%	90.80%	95.50%	96.50%

Table 3.3 depicts further descriptive statistics on the different individual roles. There are several observations from this table that are worth mentioning. First, it is useful to compare integrators and connectors. Integrators have more than double the number of ties, much higher ego-network density, and broader reach when compared to connectors. Connectors are indeed collaborating across clusters as indicated by the higher number of different components that they link and have a higher brokerage metric. Both types of relational stars show similar levels of productivity but nevertheless, their productivity is much lower than the one of star inventors. This is evidence against the idea that perhaps integrators and connectors occupy their network position because they are simply listed in many patents. Instead, it seems that it is their collaborative behavior, i.e. not their productivity, that makes them a special resource. Second, isolates have, as expected, very low levels of collaboration, reach, and brokerage and are as productive as the relational stars. Third, ambidextrous stars exhibit collaborative behavior that would put them between integrators and connectors but have slightly higher productivity levels. Finally,

the last three rows of the table provide additional important information. Individuals occupy their respective roles for 3-4 years on average and the vast majority of observations is on consecutive years. Therefore, individuals reach outlier status for a few years only (i.e. there are no stable outliers throughout the years) and when they do once, they generally don't get it back after losing it.

Table 3.4 depicts the results predicting exploratory output. Models 1, 2, and 3 present the results for the three different measures of exploratory output. I find strong support for the role of connectors (H1). Connectors are positive and significant drivers of exploratory output in all models ($p<.05$ - Models 2-3, $p<.01$ – Model 1). I also find strong support for the role of integrators (H2). Integrators are positive and significant drivers of exploratory output in all models ($p<.01$ – Models 1-3). On the other hand, isolates are significant drivers only for one measure of exploratory output ($p<.05$ – Model 3). Interestingly, star inventors appear significantly negative drivers of exploratory output in all three models.

Table 3.5 depicts the results predicting exploitative output. Models 1, 2, and 3 present the results for the three different measures of exploitative output. I find strong support for the role of productive isolates (H3). Productive isolates are positive and statistically significant drivers of exploitative output for all three different measures of such output ($p<.05$ - Models 1,3; $p<.1$ – Model 2). On the other hand, integrators and connectors have no significant effects on exploitation.

Table 3.4 Exploratory Output

Table 4 - Results of Fixed- Effects Negative Binomial Predicting Exploratory Output w/ Bootstrapped Std. Errors									
	Model 1			Model 2			Model 3		
	Exploration_1: No Self Citations			Exploration_2: No Self & Original & Citations			Exploration_3: No Self & Original		
Year Effects	Incl.			Incl.			Incl.		
DV Lagged	0.002	0.001	***	0.013	0.003	***	0.001	0.002	
Merged	-0.041	0.073		0.093	0.079		-0.057	0.073	
EU	-0.707	0.665		-0.403	0.844		-0.747	0.669	
US	0.473	0.578		-0.720	0.795		0.342	0.621	
Pharma	-0.042	0.392		-0.191	0.624		-0.448	0.633	
Total Patents	0.007	0.001	***	0.006	0.001	***	0.007	0.001	***
Exploration Alliances	0.003	0.010		0.006	0.014		0.001	0.009	
Acquisitions	-0.021	0.020		-0.031	0.023	*	-0.028	0.018	*
Inventors	-4.6E-04	3.3E-04	*	0.000	0.000		-2.8E-04	2.2E-04	
Stars	-0.010	0.005	**	-0.011	0.006	**	-0.012	0.005	**
Integrators	0.012	0.003	***	0.014	0.003	***	0.011	0.003	***
Connectors	0.013	0.005	***	0.017	0.010	**	0.018	0.009	**
Isolates	0.004	0.006		0.009	0.008		0.009	0.005	**
	N = 2115 / Groups = 105			N = 2103 / Groups = 103			N = 1961 / Groups = 104		
Note: *p<0.1, **p<.05, ***p<.01									

Table 3.6 (in the Appendix) presents the results predicting middle output: output that is neither exploratory not exploitative but rather falls in the middle of the learning continuum. I find that connectors are also significant predictors of middle output for all three different measures, integrators are significant predictors for two of them, and isolates only for one of them.

Overall, Tables 3.4-3.6 provide strong support for hypotheses H1-H3 and suggest a very interesting pattern of results: in general, integrators and connectors appear to drive exploration and isolates appear to positively affect exploitation. As patterns of individual behavior move from extreme collaboration to relative isolation, so do their effects on exploratory, on middle, and finally, on exploitative output.

Table 3.5 Exploitative Output

Table 5 - Results of Fixed- Effects Negative Binomial Predicting Exploitative Output w/ Bootstrapped Std. Errors									
	Model 1			Model 2			Model 3		
	Exploitation_1: All Self Citations			Exploitation_2: All Self & No Original			Exploitation_3: Some Self & No Original		
Year Effects	Incl.			Incl.			Incl.		
DV Lagged	-0.001	0.007		0.009	0.005	**	0.000	0.001	
Merged	-0.131	0.129		-0.103	0.099		-0.056	0.089	
EU	0.221	2.322		0.161	0.408		-0.032	0.693	
US	0.388	0.770		0.457	0.572		0.051	0.622	
Pharma	-0.360	0.480		-0.430	0.415		-0.561	0.523	
Total Patents	0.006	0.001	***	0.006	0.001	***	0.006	0.001	***
Exploitation Alliances	0.007	0.016		0.004	0.019		0.007	0.013	
Acquisitions	-0.023	0.036		-0.029	0.035		-0.024	0.027	
Inventors	-3.1E-04	3.6E-04		-6.4E-04	3.3E-04	**	-2.3E-04	2.7E-04	
Stars	0.002	0.005		0.002	0.004		-0.003	0.004	
Integrators	-0.001	0.006		0.001	0.006		0.003	0.004	
Connectors	0.004	0.010		0.006	0.010		0.007	0.009	
Isolates	0.012	0.006	**	0.009	0.006	*	0.008	0.005	**
	N = 1856 / Groups = 97			N = 2015 / Groups = 98			N = 1949 / Groups = 102		
Note: *p<0.1, **p<.05, ***p<.01									

Table 3.7 (in the Appendix) depicts results on the micro-level coordinating mechanisms predicting ambidextrous output. In Models 1-3, I include the three alternative coordination mechanisms one by one. In Model 5, I include the squared terms of the three coordination mechanisms to test for non-linear effects and I include all three coordination mechanisms together. In Model 4, I exclude some independent variables that are highly correlated with some independent variables. I find strong support for

hypotheses H4 and H5. In all models, the inventors who are at the same time exploration and exploitation stars (E-E stars) have a strong positive and significant effect on ambidextrous output ($p<.01$ - Models 1,4,5). Models 4-5 suggest that this effect may in fact be better described as an inverted-U relationship. In addition, in all models the connectedness score has again a strong positive and significant effect on ambidextrous output ($p<.05$ – Model 3; $p<.01$ – Models 4-5). Models 4-5 suggest that this effect may also be an inverted-U relationship. Somewhat surprisingly, I find a strong negative and probably linear effect of the number of ties between exploration and exploitation stars on ambidextrous output. I can speculate at this point that a high number of such ties indicates extreme separation between the two activity types which seems to be harmful for ambidexterity. Instead, as implied by the connectedness results, if the organization manages to have some level of connectedness between the two activities it reaps benefits of ambidextrous performance.

3.6. Discussion

I developed herein an evolutionary model of strategic renewal for incumbent firms operating in technologically dynamic environments. I conceptualized incumbents as large complex organizations with an existing knowledge base which includes a large portfolio of known knowledge areas. Within incumbents, individuals are organized around their knowledge domains and collaborate with each other to co-create knowledge. Radically new knowledge (i.e. exploratory output) presents opportunities for incumbents to renew their knowledge base. Instances of exploratory output trigger a cycle of strategic renewal defined here as the deliberate effort to develop radically new knowledge aimed at updating the incumbent's existing knowledge base. I looked at the internal workings of the renewal process and identified three distinct stages: first, the development of radically new knowledge stocks; second, the selection of strategically consistent and promising discontinuous knowledge stocks that require integration and the transfer of selected stocks to the firm's knowledge network; third, the incremental improvement of existing knowledge stocks. These three distinct stages correspond to three broad learning categories: exploratory, transformative, and exploitative learning. Relying on this evolutionary process of renewal, I applied insights from network and learning theory to identify the individuals, who based on their positions in the firm's internal knowledge network, have the capacity to implement the process and facilitate rapid renewal.

In particular, I emphasized the role of connectors, who bridge internal knowledge silos, and the role of integrators, who collaborate with many others internally, in facilitating exploration through distant and local knowledge recombinations, respectively. In addition, I underlined the necessity for productive isolates, who develop independent deep knowledge, when it comes to incremental improvement and exploitation. Finally, I emphasized the significance of two alternative micro-level coordinating mechanisms that can facilitate the pursuit of organizational ambidexterity. Organizations reap strong benefits of ambidexterity when they possess individuals who have the capacity to simultaneously explore for and exploit knowledge or when they retain a certain level of connectedness between their exploratory and exploitative activities.

As a result, I make several contributions to the literature. First, I develop a theory on some of organizational learning's individual microfoundations. The current research focus on individual productivity may have obscured the importance of other individual skills. Innovation is increasingly a team-based endeavor (Wuchty et al, 2007) and firms have structures, processes, and incentives to facilitate knowledge transfer and combination. Therefore, a set of collaborative skills as the ones outlined above are necessary for individuals in incumbent firms to implement the learning process. This view provides a potential explanation for recent findings that non-star scientists fully mediate the effect of stars on innovative outcomes (Rothaermel and Hess, 2007) and calls for a reexamination of the available incentive structures at firms which are focused almost exclusively on performance (Lazear, 1999).

Second, I underlined the importance of different individual skill-sets at various stages of learning (Crossan et al., 1999) and their role as drivers of radical vs. incremental learning (Gupta et al., 2006). While connectors and integrators are important for exploration, productive isolates are necessary for exploitation.

Third, I highlighted the role of individual skill-sets in promoting the balance between adaptability and efficiency by selecting and transferring discontinuous knowledge stocks that deserve internalization. I conceptualized an incumbent's internal environment as a context where individuals have the freedom to judge whether they will devote their time to radical or incremental learning (Gibson and Birkinshaw, 2004). Building on this logic, I argued for the significance of ambidextrous individuals in making the transition from change to continuity as seamless as possible. Prior research has focused on the senior management challenges in this process (Andriopoulos and Lewis, 2009; Smith and Tushman, 2005; Taylor and Helfat, 2009). Instead, here I underlined the role of knowledge-generating individuals (scientists or engineers) on the renewal of the incumbent's knowledge base. In particular, I argued that ambidexterity can result from two individual level mechanisms: first, the possession of actors who can simultaneously explore and exploit; second, a level of connectedness between actors exploring and actors exploiting.

Finally, the proposed model has implications for research in social capital, networks, and change. Social capital is developed through a number of different social relations (Adler and Kwon, 2002). Here, I relied on knowledge co-creation, which is a strong form of social capital, to develop a theory of how social capital can create human capital (Coleman, 1988). Individuals develop, through their collaborations, skills and abilities that are necessary for driving innovation-related organizational outcomes. In addition, I illustrated how micro-level network phenomena can translate into macro-level outcomes (Brass et al., 2004). Interactions within a firm's internal knowledge network result in the emergence of actors in certain network positions that are highly consequential for the performance of the organization as a whole.

3.6.1. Implications and Future Research

A very promising avenue for future research would be to study the origins of these relational stars. In the proposed model, I linked role-sets of relational stars with fundamental knowledge processes that result in the incumbent's strategic renewal. The defining characteristic for each role was the pattern of its collaborative behavior within the incumbent's knowledge network. Several important questions remain open: Where do these relational stars come from? What can managers do to get them? Star scientists seem to be driven by pure individual intellect and are a resource of given and limited supply. Therefore, incumbents can either identify them before becoming stars (Makadok, 2001) or just try to hire them away from competition (Gardner, 2005). On the other hand, relational stars can be an organizational product. What can incumbents do to internally develop relational stars?

The proposed model has implications for the broader literature on exploration and exploitation. I described here collaborative behavior by individuals which largely resembles search behavior at the firm-level across domains (Lavie and Rosenkopf, 2006). In addition, the model may also explain why some firms fail to benefit from the exploration experience (Hoang and Rothaermel, 2010) or why larger firms depend less on external knowledge for their innovations (Rothaermel and Deeds, 2004). Future research may explore how an individual level view of knowledge search may inform or benefit from insights developed in this broader literature.

3.6.2. Implications for Practice

Finally, the proposed view of strategic renewal has significant implications for managers of large incumbent firms in technologically dynamic environments. Received wisdom suggests that individual productivity is the main relevant skill for innovation and therefore incentive structures are built to maximize effort (Gibbons, 1998; Lazear, 1999). The theory developed here suggests that the sole focus on the significance of 'star scientists' may be misleading for two reasons: first, innovation is a communal endeavor and thus collaborative skills are certainly required for effective execution (Wuchty et al., 2007); second, star scientists are in limited supply and therefore they may be able to appropriate all of the value they create, leave the organization and transfer their knowledge to competitors (Almeida and Kogut, 1999), or hired away by competitors

(Gardner, 2005). As a result, star scientists can only be selected from a given pool and there is no straightforward way for managers to internally build them. On the other hand, relational stars, or actors whose performance depends on their interactions within the organization, can be an organizational product (Groysberg et al., 2008). Therefore, managers can design practices, incentives, structures, or strategic actions to internally develop individuals who address targeted learning shortcomings of their organization and benefit from a set of social and collaborative individual skills that are necessary for the effective implementation of the various stages of organizational learning.

3.7. References

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CHAPTER 3 APPENDIX

Table 3.1 Correlation Table and Descriptive Statistics

Table 1 - Correlation Table

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1. Ambidexterity	346.50	1056.77	1.00																								
2. Exploration_1	28.05	38.04	0.85	1.00																							
3. Exploration_2	5.00	7.84	0.79	0.88	1.00																						
4. Exploration_3	10.72	14.93	0.87	0.97	0.89	1.00																					
5. Exploitation_1	4.97	8.72	0.80	0.81	0.82	0.80	1.00																				
6. Exploitation_2	4.58	8.03	0.80	0.81	0.83	0.81	0.99	1.00																			
7. Exploitation_3	11.16	17.84	0.88	0.85	0.78	0.85	0.91	0.90	1.00																		
8. Total Patents	48.42	68.74	0.89	0.96	0.83	0.95	0.86	0.85	0.94	1.00																	
9. Merged	0.09	0.28	0.16	0.15	0.14	0.17	0.11	0.10	0.20	0.18	1.00																
10. EU	0.30	0.46	0.18	0.24	0.22	0.21	0.12	0.13	0.13	0.18	0.03	1.00															
11. US	0.34	0.47	0.06	0.10	0.07	0.14	0.19	0.18	0.21	0.18	0.16	-0.47	1.00														
12. Pharma	0.46	0.50	-0.17	-0.26	-0.12	-0.25	-0.14	-0.13	-0.19	-0.26	0.01	0.03	-0.06	1.00													
13. Exploration Alliances	0.62	1.43	0.21	0.21	0.21	0.23	0.18	0.18	0.24	0.22	0.24	0.01	0.11	0.02	1.00												
14. Exploitation Alliances	0.30	0.93	0.05	0.06	0.08	0.07	0.08	0.08	0.10	0.07	0.14	-0.03	0.08	0.09	0.51	1.00											
15. All Alliances	1.40	3.05	0.15	0.16	0.18	0.18	0.16	0.16	0.20	0.18	0.23	-0.02	0.13	0.06	0.87	0.74	1.00										
16. Acquisitions	0.20	0.92	0.19	0.16	0.18	0.18	0.16	0.16	0.21	0.18	0.27	0.01	0.12	0.07	0.37	0.17	0.32	1.00									
17. Inventors	222.63	274.81	0.81	0.87	0.70	0.87	0.70	0.70	0.85	0.92	0.18	0.18	0.06	-0.30	0.23	0.08	0.19	0.17	1.00								
18. Stars	3.98	10.21	0.79	0.69	0.66	0.69	0.69	0.70	0.77	0.74	0.16	0.18	0.02	-0.13	0.21	0.09	0.19	0.17	0.74	1.00							
19. Integrators	2.49	7.70	0.47	0.41	0.40	0.40	0.33	0.34	0.40	0.40	0.02	0.16	-0.17	-0.05	0.08	0.03	0.06	0.04	0.49	0.64	1.00						
20. Connectors	2.19	4.18	0.43	0.43	0.43	0.41	0.41	0.42	0.46	0.43	0.10	0.09	0.02	-0.09	0.13	0.07	0.13	0.08	0.48	0.64	0.53	1.00					
21. Isolates	1.99	3.88	0.47	0.57	0.46	0.58	0.58	0.56	0.64	0.66	0.12	0.07	0.30	-0.16	0.15	0.05	0.12	0.14	0.57	0.34	0.00	0.05	1.00				
22. Exploration Stars	23.59	35.27	0.83	0.87	0.80	0.87	0.75	0.75	0.82	0.87	0.16	0.24	0.01	-0.20	0.23	0.08	0.19	0.16	0.90	0.86	0.63	0.59	0.46	1.00			
23. Exploitation Stars	24.60	41.99	0.84	0.78	0.72	0.78	0.77	0.77	0.90	0.86	0.20	0.17	0.09	-0.17	0.27	0.12	0.24	0.22	0.89	0.90	0.58	0.60	0.50	0.90	1.00		
24. E-E Stars	6.61	14.81	0.80	0.74	0.73	0.74	0.74	0.75	0.80	0.77	0.14	0.22	0.01	-0.12	0.20	0.08	0.18	0.15	0.77	0.95	0.65	0.65	0.36	0.92	0.92	1.00	
25. E-E Ties	7.74	20.31	0.64	0.60	0.54	0.59	0.50	0.51	0.60	0.61	0.10	0.21	-0.07	-0.11	0.17	0.05	0.12	0.12	0.68	0.77	0.75	0.55	0.24	0.78	0.76	0.76	1.00
26. E-E Connectedness	0.02	0.10	-0.06	-0.09	-0.07	-0.09	-0.08	-0.07	-0.08	-0.09	-0.05	-0.05	-0.08	0.05	-0.02	-0.02	-0.03	-0.02	-0.08	-0.04	0.12	-0.04	-0.08	-0.05	-0.06	-0.03	0.12

N = 2138 observations

Table 3.6 Middle Output

Table 6 - Results of Fixed- Effects Negative Binomial Predicting Middle Output w/ Bootstrapped Std. Errors									
	Model 1			Model 2			Model 3		
	Middle_1: All Self Citations			Middle_2: All Self & No Original			Middle_3: Some Self & No Original		
Year Effects	Incl.			Incl.			Incl.		
DV Lagged	0.001	0.003		0.000	0.000		0.001	0.000	*
Merged	-0.060	0.081		-0.071	0.054	*	-0.084	0.067	
EU	-0.147	0.642		-0.651	0.505	*	-0.639	0.640	
US	0.409	0.514		0.577	0.495		0.477	0.521	
Pharma	-0.249	0.399		-0.205	0.458		-0.147	0.414	
Total Patents	0.006	0.001	***	0.007	0.001	***	0.007	0.001	***
All Alliances	-0.002	0.004		0.004	0.003		0.002	0.004	
Acquisitions	-0.013	0.029		-0.013	0.019		-0.018	0.018	
Inventors	6.6E-06	2.8E-04		-3.2E-04	2.5E-04	*	-2.5E-04	3.1E-04	
Stars	-0.006	0.003	**	-0.008	0.005	**	-0.009	0.006	*
Integrators	0.003	0.004		0.008	0.002	***	0.006	0.003	***
Connectors	0.013	0.008	**	0.013	0.004	***	0.014	0.005	***
Isolates	0.007	0.004	**	0.005	0.007		0.006	0.006	
	N = 1925 / Groups = 100			N = 2115 / Groups = 105			N = 2115 / Groups = 105		
Note: *p<0.1, **p<.05, ***p<.01									

Table 3.7 Ambidextrous Output

Table 7 - Results of Fixed- Effects Negative Binomial Predicting Ambidextrous Output w/ Bootstrapped Std. Errors

	Model 1			Model 2			Model 3			Model 4			Model 5		
Year Effects	Incl			Incl			Incl			Incl			Incl		
DV Lagged	-1.1E-05	4.7E-05		-1.6E-05	4.8E-05		-2.1E-05	4.8E-05		1.9E-05	4.4E-05		1.8E-05	4.3E-05	
Merged	-0.086	0.061	*	-0.088	0.061	*	-0.082	0.061	*	-0.086	0.060	*	-0.070	0.061	
EU	0.151	0.112	*	0.158	0.111	*	0.168	0.111	*	0.103	0.112		0.099	0.113	
US	0.730	0.100	***	0.728	0.100	***	0.742	0.100	***	0.708	0.100	***	0.713	0.100	***
Pharma	-0.459	0.088	***	-0.440	0.088	***	-0.464	0.088	***	-0.413	0.089	***	-0.422	0.090	***
Total Patents	0.010	0.000	***	0.010	0.000	***	0.010	0.000	***	0.010	0.000	***	0.010	0.000	***
All Alliances	-0.001	0.005		-0.002	0.005		0.000	0.005		0.001	0.005		0.001	0.005	
Acquisitions	-0.067	0.019	***	-0.072	0.019	***	-0.068	0.019	***	-0.045	0.017	***	-0.049	0.018	***
Inventors	-3.9E-04	2.0E-04	**	-4.2E-04	2.0E-04	**	-3.3E-04	1.9E-04	**				-5.5E-04	2.1E-04	***
Stars	-0.017	0.003	***	-0.009	0.002	***	-0.012	0.002	***	-4.2E-04	1.6E-04	***	-0.006	0.003	**
Integrators	0.007	0.003	**	0.010	0.003	***	0.008	0.003	**	0.011	0.003	***	0.009	0.003	***
Connectors	0.016	0.004	***	0.019	0.004	***	0.020	0.004	***	0.023	0.004	***	0.021	0.004	***
Isolates	0.015	0.003	***	0.017	0.004	***	0.015	0.003	***	0.018	0.003	***	0.018	0.003	***
Exploration	0.004	0.003		0.004	0.003		0.004	0.003		0.002	0.003		0.003	0.003	
Exploitation	-0.002	0.003		-0.002	0.003		-0.001	0.003		-0.001	0.003		-0.002	0.003	
ER Stars	0.003	0.001	**	0.005	0.001	***	0.004	0.001	***				0.002	0.002	*
ET Stars	0.001	0.001		0.002	0.001		0.000	0.001					0.001	0.001	
E-E Stars	0.007	0.003	***							0.022	0.004	***	0.021	0.004	***
E-E Stars Squared										-1.4E-04	1.8E-05	***	-1.2E-04	2.1E-05	***
E-E Ties				-0.003	0.001	***				-0.003	0.002	*	-0.004	0.002	**
E-E Ties Squared										-6.0E-06	1.1E-05		-2.7E-06	1.1E-05	
E-E Connectedness							0.517	0.271	**	2.145	0.633	***	2.163	0.638	***
E-E Conn Squared										-2.369	0.935	***	-2.315	0.935	***
	N = 1927 / Groups = 101			N = 1927 / Groups = 101			N = 1927 / Groups = 101			N = 1927 / Groups = 101			N = 1927 / Groups = 101		

Note: *p<0.1, **p<.05, ***p<.01

CHAPTER 4

ORGANIZING FOR CAPABILITY BUILDING: INTERNAL KNOWLEDGE NETWORKS, RECOMBINATIVE POTENTIAL, COORDINATION COSTS, AND THE EFFECTIVENESS OF EXTERNAL KNOWLEDGE SOURCING

4.1. Introduction

Competence-destroying technological change poses significant challenges on an industry's incumbent firms to innovate quickly and adapt to a new technological paradigm (Tushman and Anderson, 1986). To respond, incumbents invest in internal capability development (Tripsas, 1997), human capital (Zucker and Darby, 1997), strategic alliances (Rothaermel, 2001), acquisitions of new entrants (Higgins and Rodriguez, 2006), or in combinations of those strategies (Rothaermel and Hess, 2007). There is a significant degree of consensus in the strategy literature that successful renewal depends on incumbents developing skills in both internal knowledge development and external knowledge sourcing (Helfat *et al.,* 2007). The merits of each sourcing mode have been widely documented. Yet, we have a limited understanding about the conditions that favor one sourcing mode over others. Capron and Mitchell (2009) echo this statement when arguing that a firm's selection capability, defined as the ability to select among modes of sourcing, is an underemphasized form of capability. Further, Nickerson and Zenger (2004: 1) suggest that 'the key knowledge-based question the manager faces is not how to organize to exploit already developed knowledge or capability, but rather how to organize to efficiently *generate* knowledge and capability'. In this study, we aim to contribute to this line of work and examine how the effectiveness of external knowledge sourcing depends on the state of a firm's internal capabilities in developing knowledge in a new technological paradigm.

Two theories have been applied to explain and predict those knowledge boundary choices. On one hand, transaction cost (TC) theory suggests that firms choose by comparing the cost between different modes, cost that is largely driven by asset specificity and the potential for opportunism (Williamson, 1975; 1985). On the other hand, the capabilities-based (CB) view suggests that firms choose based on comparative capability considerations, which depend on the complementarity between target-knowledge and the existing knowledge base (Kogut and Zander, 1992). Despite their dominance in the knowledge boundary discussion, both theories have been criticized for various shortcomings. Scholars have argued that TC thinking overlooks the internal functioning of organizations (Gibbons, 1999), neglects the social aspect of knowledge production (Foss, 1999), and underestimates the production costs involved in qualitative coordination (Langlois and Foss, 1999). On the other hand, scholars conclude that the CB logic, though seemingly more suitable to the question of knowledge sourcing boundaries, is still weak as a theory of economic organization because it suffers from a lack of agreement on the microfoundations of capabilities (Felin and Foss, 2005), fails to explain how transaction costs and capabilities co-evolve to determine boundaries (Jacobides and Winter, 2005), and is unable to explain why certain boundary choices persist even after the development of internal capabilities (Argyres and Zenger, 2011). To resolve empirical puzzles and theoretical challenges, scholars identified potential value in an effort to integrate the two competing perspectives and examine capabilities, costs, and boundary choices as intertwined in a dynamic manner (Foss, 1999, Madhok, 2002, Jacobides and Winter, 2005).

In this study, we integrate insights from both theoretical perspectives to predict the effectiveness of external knowledge sourcing strategies for incumbent firms trying to develop knowledge in a new technological paradigm. We rely on the knowledge produced in these firms to capture the state of their internal capabilities. In particular, we track the emergent internal inter-personal network of knowledge generation to capture internal functioning, knowledge production costs, and emphasize the socially-intensive process of knowledge generation. Our core argument is that external knowledge sourcing strategies (i.e. alliances or acquisitions) to build new capabilities are less effective for firms which already possess high potential for internal knowledge recombination or high coordination costs in their knowledge generation process. To proxy for these two dimensions of a firm's state of internal capabilities, we look at the micro-structure of their knowledge network and the presence of critical individual roles; more specifically, we focus on structures and individuals which have been shown to represent high recombinative potential or coordination costs. Therefore, we explicitly look at the microfoundations of internal capabilities and we argue that differences across firms in these microfoundations are another driver of the effectiveness of external knowledge sourcing choices. In addition, we examine the phenomenon using a large multi-firm longitudinal sample, we continuously update the internal knowledge network to address the co-evolution of capabilities and knowledge sourcing choices, and we explain why certain choices persist even after the development of internal capabilities. Overall, we take an atomistic knowledge-based view and argue that it is the state of internal capabilities that dictates the effectiveness of external knowledge sourcing for incumbents trying to adapt to a changing knowledge paradigm.

To be sure, this question of complementarity between internal and external knowledge sourcing has received some attention in the literature. Research has documented that the degree of complementarity depends on intellectual property considerations and the basicness of the R&D base (Cassiman and Veugelers, 2006), the firms' absorptive capacity (Cohen and Levinthal, 1990), interactions across levels of analysis (Rothaermel and Hess, 2007), capability differences across vertical value chain segments (Jacobides, 2008), or the type of experience in different learning stages (Hoang and Rothaermel, 2010). The idea that it is differences in internal capabilities that essentially drive boundary choices has also been documented before (Jacobides and Hitt, 2005; Jacobides and Winter, 2005). The novelty in our study results from the application of social network theory to develop a fine-grained picture of the state of a firm's internal capabilities, capture potential for knowledge recombination and coordination costs, and document the role of the structure of a firm's internal knowledge network as a driver of the effectiveness of that firm's external knowledge sourcing choices.

To overshadow our conclusions, we argue that selecting the most efficient way to develop new knowledge is a highly consequential strategic capability. Although external sourcing using alliances or acquisitions has well-documented independent benefits for new knowledge generation, we argue here that it is not as efficient when combined with a healthy state of internal capabilities. We test our theoretical framework in the global pharmaceutical industry: we track the innovative activities of 106 incumbent firms, in their effort to adapt to the biotechnology paradigm, for a period of 25 years (1974-1998).

We rely on these firms' patenting portfolios and individuals inventors to build internal networks of biotech knowledge generation. We apply network theory to extract information from these networks about the firms' knowledge recombinative potential, coordination costs, and possession of critical individual roles. We predict their capacity to develop biotech knowledge by combining external knowledge sourcing with various states of internal capabilities. We show that alliances and acquisitions are less effective as modes of knowledge generation when the focal firm has an internal knowledge network with recombinative potential or high coordination costs and when the focal firm already has inventors who exhibit the capacity for effective future knowledge recombination. In addition, we uncover interesting differences in these interactions between alliances and acquisitions thus confirming the heterogeneity in the nature of knowledge generation between these two sourcing modes. We discuss implications of our work for the theories on boundary choices for knowledge generation. Finally, we highlight managerial implications about the effectiveness of combining knowledge sourcing modes for capability development and adaptation.

4.2 Theory and Hypotheses

One of the most enduring themes in strategy research is the mandate for incumbent firms to undertake capability sourcing strategies either internally or externally in the face of an environmental discontinuity (Agarwal and Helfat, 2009). A capability to execute both modes effectively is necessary especially in today's science-based business environment (Pisano, 2010). For example, internal development of knowledge is important either because firms are better at coordinating generation of new knowledge

(Grant, 1996) or because they need a certain level of internal understanding to evaluate external knowledge opportunities (Cohen and Levinthal, 1990), among other reasons. External knowledge sourcing is important to prevent obsolescence and encourage acquisition of knowledge that is largely dissimilar to the firm's existing knowledge base (Rosenkopf and Nerkar, 2001), among other reasons.

One of the questions that has received significant attention is how firms choose their knowledge boundaries for new capability development. Scholars have examined the relative explanatory power of transaction cost and knowledge-based theories in predicting make-or-buy decisions (Poppo and Zenger, 1998). We know that firms may favor external sourcing because of a preference for outsiders' knowledge (Menon and Pfeffer, 2003), internal social comparison costs (Nickerson and Zenger, 2004), or availability of knowledge suppliers and an intense competitive environment (White, 2000). Firms may choose external sourcing because of dyadic considerations like knowledge fit (Baum, Cowan, and Jonard, 2010), status similarity (Chung, Singh, and Lee, 2010), or mutual trust through fairness (Arino and Ring, 2010) with potential partners. Firms may also rely on external sourcing because of their prominent position in interfirm networks (Gulati, 1999; Yang, Lin, and Lin, 2010). Alternatively, more atomistic explanations like the depth of the firm's internal knowledge base have also been documented as drivers of the internal vs. external sourcing choice (Zhang and Baden-Fuller, 2010). Finally, there is also research that attempts to explain the preference for certain external sourcing modes over others (e.g. alliances vs. acquisitions) (Hagedoorn and Duysters, 2002; Vanhaverbeke, Duysters, and Noorderhaven, 2002).

In parallel, several insightful studies have addressed the question of implementation, that is, how can firms effectively use different external sourcing modes to build new capabilities. For example, research has shown how firms can maximize the effectiveness of alliances by altering their intra-alliance value appropriation (Adegbesan and Higgins, 2011), their scope (Oxley and Sampson, 2004), or their learning objectives (Rothaermel and Deeds, 2004). In addition, others have documented how firms can increase the benefits of acquisitions by increasing the size of the acquired knowledge base (Ahuja and Katila, 2001), by acquiring information about the targets' R&D activities prior to the acquisition (Higgins and Rodriguez, 2006), by relying on complementary knowledge (Makri, Hitt, and Lane, 2010), or by altering the level of post-acquisition integration (Puranam, Singh, and Chaudhuri, 2009). Finally, we know how firms can make contracting more effective through repeated exchange and learning (Mayer and Argyres, 2004; Argyres, Bercovitz, and Mayer, 2007). Overall, research has resulted in an understanding of the factors that drive knowledge boundary choices and of the levers that can increase the effectiveness of various knowledge sourcing initiatives.

However, there is mounting evidence that firms increasingly rely on a combination of internal and external sourcing (Parmigiani, 2007). Beyond understanding how firms choose their knowledge boundaries and examining ways to increase the effectiveness of independent knowledge sourcing strategies, we also need to investigate the conditions that make certain sourcing modes more appropriate than others when combined with the firm's existing stock of capabilities. Recently, Capron and Mitchell (2009) echo this statement and they argue that a firm's ability to select the right mode of capability sourcing under different circumstances is a capability that remains underemphasized.

This is where our study aims to provide a contribution. We rely on an atomistic knowledge-based conceptualization of the firm and its knowledge-sourcing choices. We observe that firms, following internal knowledge development or previous external knowledge sourcing choices, find themselves endowed with a certain level of internal capabilities for knowledge generation. We argue that it is the state of these internal capabilities that dictates the effectiveness of alternative external knowledge sourcing modes. Importantly, by choosing this atomistic view, we do not reject the importance of the aforementioned dyadic or network views; instead, we believe that the atomistic view suits our objective, which is to emphasize the selection issue: when firms possess certain internal capabilities, simply selecting external knowledge sourcing may be more or less appropriate for new capability building.

Essentially, we attempt to address the question of organizational design for capability building (Madhok, 2002). Differences in capabilities determine boundaries (Jacobides and Hitt, 2005) and boundary choices in turn, affect the capability building process (Jacobides and Winter, 2005). There is evidence that this co-evolution of boundaries and capabilities when firms choose their vertical scope affects their prospects for capability building (Jacobides and Billinger, 2006). Here, we focus on a similar interaction between capabilities and knowledge sourcing choices when firms choose their *knowledge* scope. We track a firm's constantly updating internal knowledge base and we argue that the effectiveness of external knowledge sourcing depends on attributes of that firm's knowledge base: more specifically, the firm's capacity for internal knowledge recombinative potential and the associated coordination costs. We suggest that external sourcing is less effective when the firm has internally the capacity for future knowledge recombination and/or when the firm's knowledge generation process is characterized by a high level of coordination costs. This is similar to what Williamson (1991) described as first-order economizing, that is, efficiently organizing for effective adaptation.

Arguably, this is also related to the question of complementarity between internal and external capability sourcing. Despite a lack of emphasis on this problem, we do have evidence about factors that affect the degree of complementarity: the basicness of R&D and intellectual property considerations (Cassiman and Veugelers, 2006), careful orchestration of innovation strategies across levels of analysis (Rothaermel and Hess, 2007), or across structural and functional domains (Lavie and Rosenkopf, 2006). In addition, there are also two insightful studies that are much closer to our paper in that the authors explicitly examine the effectiveness of external knowledge sourcing under various internal organization conditions. Nickerson and Zenger (2004) argue that is the problem type (e.g. its level of decomposability) that dictates the efficiency of alternative knowledge sourcing strategies. Capron and Mitchell show that the effectiveness of external renewal modes in building new capabilities depends on the size of the capability gap between current and needed capabilities and on the level of internal constraints that arise for the internal social context. In this study, we highlight the importance of two additional internal attributes: the firm's potential for future knowledge recombination in the new knowledge area and the coordination costs associated with its internal knowledge generation process. More importantly, our specific contribution is the application of social network techniques to capture recombinative potential and coordination costs and in turn, show how these two factors drive the effectiveness of external knowledge sourcing strategies.

There is evidence that one of the first strategies of incumbent firms faced with a technological discontinuity is to heavily invest in internal capability development to generate knowledge and innovate in the emerging paradigm (Argyres and Liebeskind, 2002). There is also evidence that knowledge generation has increasingly become a communal team-based endeavor (Wuchty, Jones, and Uzzi, 2007). Incumbents design structures internally to stimulate knowledge recombination and reconfiguration (Henderson and Clark, 1990; Henderson and Cockburn, 1994). In other words, as incumbents make an effort to adapt to a changing technological environment and as a result of their internal or external sourcing investments, individuals within incumbents collaborate to develop new knowledge. At the firm level, this activity of interpersonal collaboration results in extensive knowledge networks with the objective of new knowledge generation. The nodes of these networks are individuals participating in knowledge production and ties between individuals reflect direct collaboration with the objective of knowledge co-creation. Research suggests that collaborative ties can be viewed as strong ties (Hansen, 1999) that are necessary for potential knowledge recombination (Galunic and Rodan, 1998). We examine the structure of these knowledge networks to capture the firm's recombinative potential and level of coordination costs.

First, a network's structure is important for the network's overall knowledge performance. A relaxed structure facilitates improvisation (Brown and Eisenhardt, 1997), a cohesive structure positively affects individuals' capacity to transfer knowledge (Reagans, Zuckerman, and McEvily, 2004), network heterogeneity drives learning (Reagans and Zuckerman, 2001), and network range supports knowledge transfer (Reagans and McEvily, 2003). A network which is nearly decomposable, i.e.

characterized by cohesive clusters linked with cross-cluster ties, is the most effective for generation of useful new knowledge (Yayavaram and Ahuja, 2008). Finally, efficiently structured networks perform better in the short run while effectively structured networks are more appropriate for long run performance (Lazer and Friedman, 2007).

Here, we build on this line of work and examine structural attributes of an incumbent firm's knowledge network, attributes which can be linked with the firm's potential for future knowledge recombination. We conceptualize the process of new knowledge production as a structural knowledge-based process of recombination of existing knowledge stocks (Fleming, 2001). In particular, we focus on two dimensions: the degree of the network's clustering and its average path length. A highly clustered network indicates a structure that is abundant with cohesive micro-clusters of knowledge production which have been shown to facilitate future knowledge recombination. Average path length captures the average distance between any two actors in the network. Longer paths indicate a network that is largely heterogeneous, has extensive range, and relies on significant breadth of knowledge stocks. Taken together, we argue that if a firm has an internal knowledge network with high clustering and average path length then that firm has significant potential for internal future knowledge recombination and in turn, makes external sourcing strategies less effective for new capability building. External sourcing results in infusion of new knowledge (e.g. alliances) or new knowledge-producing talent (e.g. acquisitions). However, a firm cannot follow every possible knowledge trajectory suggested by its internal development process and external sourcing. Therefore, we posit that if a firm has internally the potential for new knowledge then external sourcing strategies will be less effective for new knowledge development.

Hypothesis 1: Under circumstances of a radical technological discontinuity, external knowledge sourcing strategies (i.e. alliances or acquisitions) are less effective for incumbent firms' new knowledge development when combined with an internal knowledge network that has high knowledge recombinative potential (i.e. high clustering and/or high average path length).

While the structure of the knowledge network has been previously used to predict its knowledge generation performance, it has not been relied upon to capture the level of internal coordination costs. In fact, scholars argue that the importance of coordination costs associated with internal knowledge production has generally been neglected by the theories of boundary choice (Langlois and Foss, 1999). Yet, Argyres and Silverman (2004) find that if a firm has a centralized R&D structure then it generates more impactful innovations through a reduction in internal coordination costs. In addition, Rawley (2010) documents how increases in internal coordination costs constrain economies of scope. We build on these insights and argue that if an incumbent firm produces knowledge in an emerging knowledge area with already high internal coordination costs, then external knowledge sourcing strategies are likely to be less effective for new capability building, because they would simply add to the coordination burden. To capture these coordination costs, we rely on two dimensions of the firm's internal knowledge network: the overall density of collaboration and the average number of collaborative ties required for a new knowledge stock. The network's overall density is the ratio of total collaborative ties to the number of individuals participating in the knowledge production process. Elevated density suggests that the organization faces a significant coordination burden as there are more ties on average for every knowledge-generating individual. The average number of ties per new knowledge stock, similarly, suggests elevated coordination costs as every new knowledge stock requires a higher, on average, level of interpersonal collaboration.

Hypothesis 2: Under circumstances of a radical technological discontinuity, external knowledge sourcing strategies (i.e. alliances or acquisitions) are less effective for incumbent firms' new knowledge development when combined with an internal knowledge network that has high coordination costs (i.e. high density and/or average collaborative ties per new knowledge stock).

We now shift our focus away from the structure of the overall firm-level knowledge network to identifying specific individuals roles in the network that would indicate the presence of internal recombinative potential. We make an effort to identify individuals, who based on their extreme collaborative behavior, have the potential for effective future knowledge recombination. In essence, we try to identify individuals-outliers in three meaningful dimensions of collaborative behavior and argue that firms possessing these individuals have better prospects for internal knowledge recombination and therefore, will benefit less from external knowledge sourcing. The shift from average firm-level network structure serves two objectives: a theoretical and a practical one. On one hand, by looking at individuals we examine the realistic locus of knowledge generation which is at the individual level of analysis (Felin and Hesterly, 2007). Therefore, we uncover the microfoundations of a firm's internal capabilities not only by looking at firm-level network micro-structures but also by searching deeper for specific individual attributes.

On the other hand, the practical aspect of this endeavor relates to additional insights that can be gained by looking at individuals and goes beyond firm-level averages. This is essentially the difference between looking at a distribution's mean and its variance. Firm-level network averages correspond to the mean level of recombinative potential and coordination costs. Capturing individual outliers allows us to go beyond that and examine the variance of these two distributions. It suffices to think that for an individual every new additional tie results in an exponential increase in the number of potential recombinations that can be identified by that specific individual. We focus on three types of such important individual roles.

First, we look at individuals who drive the formation of clustering; we call them integrators to reflect their function of effectively integrating different knowledge stocks. Integrators are the actors who have an extraordinarily large and dense network of collaborators relative to their peers in every other competing organization. Integrators operate as the glue that holds together the dense clusters of interpersonal collaboration. We argue that the presence of integrators in a firm's knowledge network reflects solid potential for future knowledge recombination achieved at high levels of coordination costs. Through their many collaborative ties, integrators source knowledge from multiple sources and therefore have the capacity for identifying promising potential recombinations. In addition, they have a broad picture of who knows what and can highlight promising avenues for recombination that can then be attained by their alters. This view is consistent with evidence that knowledge from central actors in a firm's network is more likely to be found in the firm's future knowledge capabilities (Nerkar and Paruchuri, 2005).

Second, we look at individuals who drive distant knowledge recombination; we call them connectors to emphasize their capacity to connect disparate pieces of knowledge in order to create something new. Connectors are the actors who, through their collaborative behavior, span internal structural holes, link previously unconnected knowledge stocks, and access diverse and distant clusters of knowledge. We also argue that the presence of connectors in a firm's knowledge network suggests strong potential for future knowledge recombination and high coordination costs. Connectors engage in novel knowledge recombinations which arguably open up unexplored avenues for further knowledge recombination which can be done by them or others in the firm's network. While not necessarily extremely collaborative, connectors do indicate high coordination costs as they link dissimilar stocks of knowledge that may belong to different thought worlds. This view is also consistent with existing evidence showing that individuals who span structural holes develop better ideas (Burt, 2004), are more creative (Fleming, Mingo, and Chen, 2007), and perhaps more importantly for our purpose, adapt better to changes in their task environment (Gargiulo and Benassi, 2000).

The third type of individual actors that we focus on is the role played by isolates. Isolates are actors who while producing new knowledge for the firm, remain unconnected from the firm's knowledge network. In other words, these individuals produce knowledge independently without any collaborative ties. Apparently, isolates are not in a position that would allow them to recombine of knowledge stocks sourced from their alters. However, their presence in a firm's knowledge network does suggest the potential for future knowledge recombination, albeit with minimum coordination costs. Isolates represent sources of new knowledge, as they are somewhat productive, that remain unconnected from the network. Therefore, they reflect the possession of a source of knowledge generation which could potentially enter the firm's recombinatory process at any future point time and result in the creation of further avenues for knowledge recombination. As a result, these individuals-outliers in terms of a lack of collaborative behavior also indicate strong recombinative potential for their firm. Taken together, the three types of individuals capture firm-level internal resources with solid potential for further knowledge recombination achieved mostly at high coordination costs thus negatively affecting the effectiveness of external knowledge sourcing strategies.

Hypothesis 3: Under circumstances of a radical technological discontinuity, external knowledge sourcing strategies (i.e. alliances or acquisitions) are less effective for incumbent firms' new knowledge development when combined with an internal knowledge network that is rich in individuals with extreme patterns of collaborative behavior, patterns which indicate their capacity to provide their firms with high recombinative potential and/or coordination costs (i.e. integrators, connectors, and isolates).

4.3. Methods

We test the developed hypotheses in the global pharmaceutical industry. The industry experienced a radical competence-destroying technological discontinuity with the emergence of biotechnology. Large incumbent pharmaceutical firms faced tremendous pressures to adapt to the new technological paradigm because their upstream research capabilities were inconsistent with the new technology. Pharmaceutical incumbents invested in internal research, in human capital, in exploitation alliances to exploit their existing complementary assets, in exploration alliances to build additional technological capabilities, and in acquisitions of smaller biotechnology firms (Pisano, 2006). Therefore, we submit that this industry is an ideal setting to test our hypotheses about the interaction between external sourcing and internal capabilities. Following investment in internal development and/or external knowledge sourcing, pharmaceutical incumbents firms were able to slowly build internal capabilities in generating biotech-related knowledge and adapt to the technological discontinuity. We track this process of internal development to capture the state of internal capabilities in the emerging paradigm and examine the effectiveness of various external knowledge sourcing strategies.

Our initial sample consisted of 106 incumbent pharmaceutical firms worldwide, a sample which is representative of the global pharmaceutical industry. We characterize those firms as incumbents as they were active in the pharmaceutical industry focusing on human therapeutics prior to the emergence of biotechnology. We collected annual data for the sourcing strategies of those firms beginning in 1974 until the end of 1998. The year 1974 closely approximates the beginning of industry research in biotechnology, one year after the invention of a technique to recombine DNA developed by Cohen and Boyer in 1973. Several firms from our sample did not develop a significant presence in biotechnology and therefore, their biotech patents were not enough to generate meaningful internal knowledge networks. We excluded these firms from our analysis and thus our final sample consists of 96 pharmaceutical incumbents. Horizontal mergers are a common incident in this industry; when a merger occurs we combine the data of the merging firms into one entity, we continue tracking it forward, and we create an indicator variable to capture a merged entity.

We constructed the key dependent and independent variables relying on patents granted to these firms by the USPTO. Despite some problems, patents have been extensively used to measure a firm's innovative activities (e.g. Ahuja, 2000; Henderson & Cockburn, 1994). In addition, the pharmaceutical industry is the industry which 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 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 have each firm's full patenting activity.

4.3.1. Dependent variable

To capture the successful development of knowledge capabilities in the emerging biotech paradigm by pharmaceutical incumbents, we relied on the annual count of biotech patents assigned to the firms in our sample. To define which of the patents in an incumbent's patent portfolio are biotech patents, we relied on the definition of a biotech patent provided by the Patent Technology Monitoring Division (PTMD) of the U.S. PTO. The Division provides a list of technology classes and sub-classes that capture new knowledge stocks with a strong biotech component. To confirm the validity of this approach, we examined the patent portfolios of dedicated biotechnology firms and the technology classes to which their patents are assigned and we found that indeed, our approach of categorizing biotech patents was robust. Finally, to make sure that our measure is as close as possible to the actual date of knowledge generation, we constructed our measure of annual biotech patent counts based on the application date of the patent instead of the grant date.

4.3.2. Intrafirm Knowledge Networks in Biotechnology

To capture the state of internal capabilities of incumbent firms in the biotechnology paradigm and develop our independent variables, we developed intrafirm co-inventing networks for each incumbent firm from 1974 to 1998 based only on their biotech patents. Hence, we were able to proxy the level of internal collaboration and capability development in biotechnology by looking at the emerging intrafirm co-inventing networks developing in the context of the new technological paradigm. We identified unique individual inventors on these biotechnology patents using the NBER database inventor file based on a combination of last name, first name, and middle name after fixing the spelling mistakes which existed in the database (Hall et al. 2001). When there was still a conflict, we expanded our matching criteria to include city and state of residence for each inventor. The resulting dataset is a file for every firm with unique inventor IDs associated with patents from 1974 to 1998.

We used UCINET 6 to create the co-inventing networks. The nodes of the network are individual inventors and a tie between inventors represents a co-patenting event. We considered knowledge through a tie that is older than five years as out-of-date and thus we developed networks for every firm using a 5-year rolling window and assigned the resulting values to the last year of every time window (82-86 values to 1986, 83-87 values to 1987, etc.). We analyzed the networks and kept several network metrics either at the firm-network level (density, average path length, etc.) or at individual-node level (e.g. ego-network attributes) to construct the following independent variables for our study.

4.3.3. Independent variables

We used the results of our network analysis to capture two main attributes of an incumbent firm's state of internal biotech capabilities: recombinatory potential and coordination costs. We measured these two attributes both at the firm level and at the individual level of analysis and used several variables for each one.

First, at the firm-network level of analysis we measured coordination costs using two different metrics: average ties per biotech patent and network density. Our objective was to capture the coordination burden of the firm as it develops new biotech knowledge internally. *Average ties per biotech patent* is one aspect of the coordination burden as it reflects the average intensity of collaboration used to generate a biotech patent. Using the previously mentioned five-year rolling window procedure, in order to come up with our variable for year t, we divided the total number of collaborative ties used to develop biotech patents from year t-4 to year t by the number of biotech patents produced in year t. *Network density* is a second aspect of the coordination burden as it reflects the average intensity of collaboration per inventor. To construct the density variable, we divided the same total number of collaborative ties by the total number of inventors participating in the knowledge production process during the same five-year window (i.e. the size of the network).

Second, again at the firm level of analysis, we measured the firm-network's recombinatory potential using two other network metrics: average path length and degree of clustering. *Average path length* is the average distance (steps through ties) between any two inventors in the firm's knowledge network. The higher this average length, the broader is the firm's knowledge network base and therefore, the higher is the potential for further knowledge recombination. *Clustering* is the degree to which the firm's network is organized around multiple local neighborhoods of dense interpersonal collaboration, where arguably knowledge recombination is more likely to occur since those clusters are more likely to be characterized by increased motivation to share knowledge, transfer knowledge transfer, and knowledge of who knows what.

Third, at the individual level of analysis, we first identified the individuals, who are universal collaborative outliers in three meaningful distributions, and therefore, play the roles of integrators, connectors, and isolates. 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 five-year window. Then, among the resulting set of actors, we characterized as integrators the inventors at the top half of the density distribution with more than one patent during the time window (to exclude one-time inventors). Therefore, *integrators* are the actors who are outliers in terms of the size and density of their ego-network and therefore, have the capacity for solid local knowledge recombination. At the same time, integrators face high coordination costs in their recombinatory efforts and are arguably relatively more firm-specific than other actors because they rely on a bigger group of collaborators to generate new biotech knowledge.

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 all inventors from all firms during the same five-year time window. Hence, we sampled on inventors who span structural holes. Among them, we selected inventors whose two-step reach was at the top half of the reach distribution. Therefore, among the inventors who spanned 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. As a result, *connectors* are outliers in terms of cluster-bridging behavior, thus being in a position to engage in strong distant knowledge recombination. At the same time, connectors face a high level of coordination costs because they link dissimilar knowledge stocks and collaborate across heterogeneous thought-worlds.

Empirically defining *isolates* was a relatively more straightforward exercise. We selected inventors with more than one patent in the same five-year time window (to exclude one-time inventors) while unconnected from the firm's network (that is, zero ties). Isolates reflect a high level of recombinatory potential obviously not because of their own recombinatory efforts; instead, they reflect the presence of knowledge-producing talent that has yet to be included in the overall firm's process of knowledge recombination. Using these variables at the inventor level, we developed variables at the firm level using counts of *integrators, connectors*, and *isolates*, that each firm possesses in each year from 1974 to 1998 (again counts from time window 74-78 go to 1978, counts from 75-79 go to 79, etc.).

Next, we collected information about the external knowledge sourcing strategies that were undertaken by the pharmaceutical incumbents in our sample. We focused on two such external capability sourcing modes: knowledge-oriented alliances with sources of biotech knowledge (i.e. exploration alliances) and biotech-related acquisitions. First, we collected data on the alliance history for every firm in our sample from the BioScan directory and the ReCap database, databases that have been successfully used in prior research on alliances and are considered to be the most comprehensive sources for alliance activities. Then, we selected all the alliances that incumbent firms in our sample entered with various sources of biotechnology knowledge (smaller entrants, universities, and other institutions). Following a common procedure in prior research (Koza & Lewin 1998, Rothaermel & Deeds 2004; Lavie & Rosenkopf 2006) 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. To ensure correct coding, we used multiple research assistants who coded independently the alliances in our sample and the inter-rater reliability was 98%, well above the recommended 70% (Cohen et al. 2003). The resulting variable is an annual count of the total number of such exploration alliances entered by an incumbent firm in our sample. Further, we relied on the SDC Platinum database for data on acquisitions and we collected information about the annual *number of biotech-related acquisitions* made by incumbent firms in our sample. Finally, to construct the independent variables and test our hypotheses, we calculated interactions between the two types of external knowledge sourcing and the three sets of internal capability attributes we mentioned earlier. Before entering them into interactions, we standardized all variables.

4.3.4. Control variables

We control for the effect of the firm's overall *innovative performance* by including as a right-hand side variable the flow of its overall patents (including biotech patents). We also control for the firm's relative focus on the generation of biotech knowledge by including a *biotech focus* ratio, the number of biotech patents divided by total patents. Prior experience in external sourcing is also likely to have an effect on both future knowledge sourcing choices and current internal capabilities, so we also control for *the firm's experience with exploration alliances and biotech-related acquisitions* by including the running stock of such previous external sourcing activities. To control for other aspects of the firm's existing knowledge-producing resources, we include the number of total inventors and the number of star inventors. The number of total inventors captures at the same time each five-year *network's size,* which is arguably one of the main drivers for the presence of the various individual roles. *Star inventors* counts inventors with patents that are three standard deviations above the mean number of patents of every other inventor in the same five-year time window. In addition, we control for the firm's geographic origin (*EU, US*). Finally, we include indicator variables that control for firms that were a result of an horizontal merger (*merged firm*) and firms that are dedicated pharmaceutical firms, that is, not diversified conglomerates (*Pharma*).

4.3.5. Estimation

Our dependent variable is a nonnegative count variable with overdispersion and therefore, we used negative binomial models. Both fixed- and random- effects specifications would allow us to control for any remaining unobserved heterogeneity. We conducted a Hausman test which suggested that there are no significant differences between the two estimation methods. Nevertheless, we chose to rely on a firm fixed-effects specification to conduct a conservative within-firm analysis and control for firm-level unobservable factors. However, as a robustness check, we also used the random-effects specification and our results remained robust.

4.4. Results

Table 4.1 (in the Appendix) depicts descriptive statistics and bivariate correlations for our variables. Correlations among our independent variables are below the recommended ceiling of 0.70. To further evaluate the threat of collinearity, we estimated the variance inflation factors (VIFs) for each coefficient, with the maximum estimated VIF being 1.64, which is well below the recommended threshold of 10 (Cohen *et al*., 2003). Table 4.2 (in the Appendix) depicts the results of our fixed-effect negative binomial regression predicting the number of incumbent firm-level biotech patents. In Model 1, we only included control variables. In Model 2, we added the interactions between external knowledge sourcing and firm-level network variables. In Model 3, we instead added only the interactions between external knowledge sourcing and individual-level capability variables. In Model 4, we included all the interactions together. We discuss below the results from Model 4 which is the all-inclusive one.

External knowledge sourcing is generally effective for capability building as both exploration alliances and acquisitions are positive drivers of biotech patent output ($p<0.1$ and $p<0.01$, respectively). The two variables capturing the level of internal coordination costs (i.e. average ties per patent and network density) are negatively and significantly related to biotech patent output ($p<0.001$). This is evidence of the coordination burden in the process of knowledge generation in an emerging technological paradigm. The first proxy of a firm's internal recombinatory potential (average path length) is as expected positively and significantly associated with biotech patent output ($p<0.01$). This result suggests that the breadth of a firm's knowledge base facilitates new knowledge generation. On the other hand, the second proxy for recombinatory potential (clustering) shows a surprising negative and significant effect on output ($p<0.001$). This result suggests that increased clustering may indicate a knowledge base that is overly focused on a few knowledge areas and therefore suffers from possible competence traps. Finally, the three types of individual roles (integrators, connectors, and isolates) are, as expected, positively and significantly related to biotech patent output ($p<0.05$, $p<0.01$, $p<0.05$, respectively).

We now shift attention to the corresponding interaction effects to test our hypotheses about the effectiveness of external knowledge sourcing under different internal capability circumstances. We find partial support for our Hypothesis 1 regarding the negative moderation effect of internal recombinatory potential. Exploration alliances are less effective when combined with high internal average path length ($p<0.01$) and clustering ($p<0.05$). On the other hand, acquisitions appear to be more effective when combined with high internal average path length ($p<0.01$). We also find partial support for our Hypothesis 2 regarding the negative moderation effect of internal coordination costs. Exploration alliances are less effective when combined with a high level of average ties per patent ($p<0.1$) and the same holds for acquisitions ($p<0.1$, Model 2). On the other hand, acquisitions appear to be more effective when combined with a dense internal network ($p<0.01$). Finally, we find support for Hypothesis 3 regarding the negative moderation effect of the three individual roles. Exploration alliances are less effective when combined with an internal network rich in connectors ($p<0.01$), while acquisitions are less effective when combined with a network rich in integrators ($p<0.05$) or isolates ($p<0.05$).

Overall, the pattern of results suggests a view which is generally consistent with our theory. However, the results also point to an interesting observation: the interaction between internal and external sourcing differs between exploration alliances and acquisitions. This is not too surprising; exploration alliances have relatively longer-term effects resulting from new knowledge infusion. On the other hand, acquisitions have shorter-term effects resulting from new knowledge-producing talent infusion. If viewed in this way, the results suggest an additional interpretation: the long-term positive knowledge effects of exploration alliances are generally reduced when combined with high internal recombinatory potential and coordination costs. On the other hand, the short-term talent infusion benefits of acquisitions are even more pronounced when the firm's network needs talent infusion to broaden its knowledge base and escape competence traps (i.e. high network density) or when the firm's network has the necessary breadth to absorb the infusion of talent (i.e. high average path length). Nevertheless, the benefits of acquisitions are reduced when the firm's network is already rich in high-potential in recombination individuals (integrators) or in productive, yet untapped, talent (isolates).

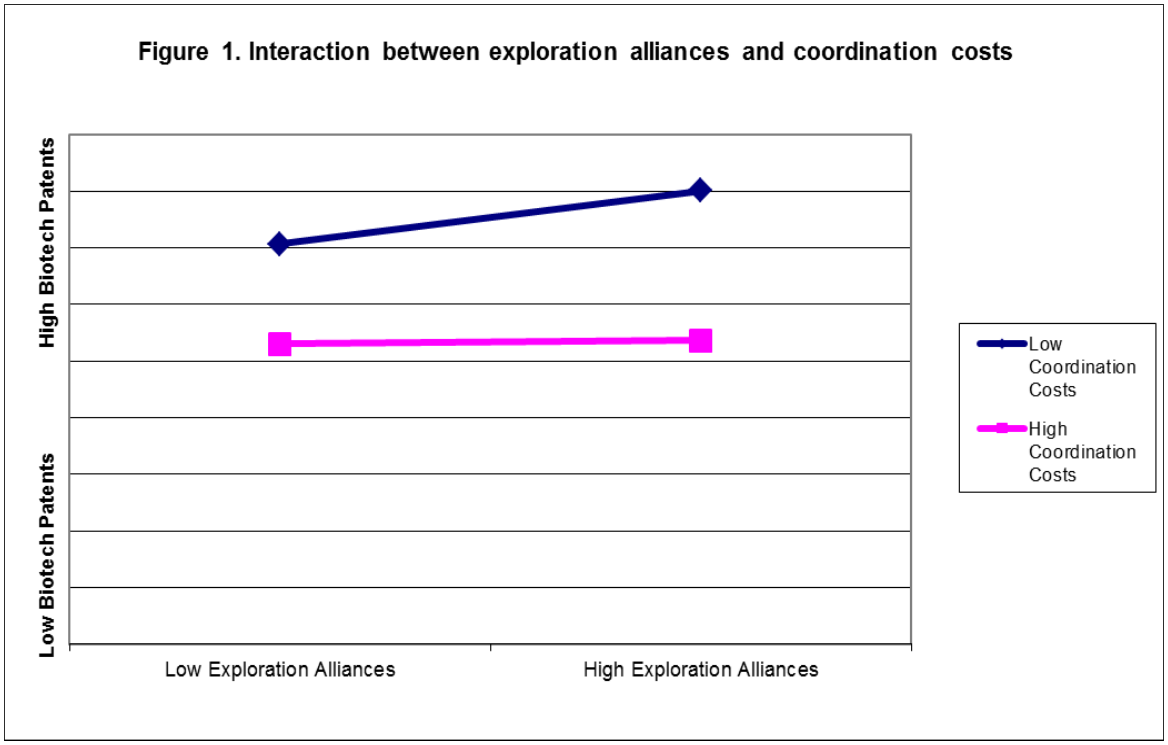

Figure 4.1. Exploration Alliances and Coordination Costs

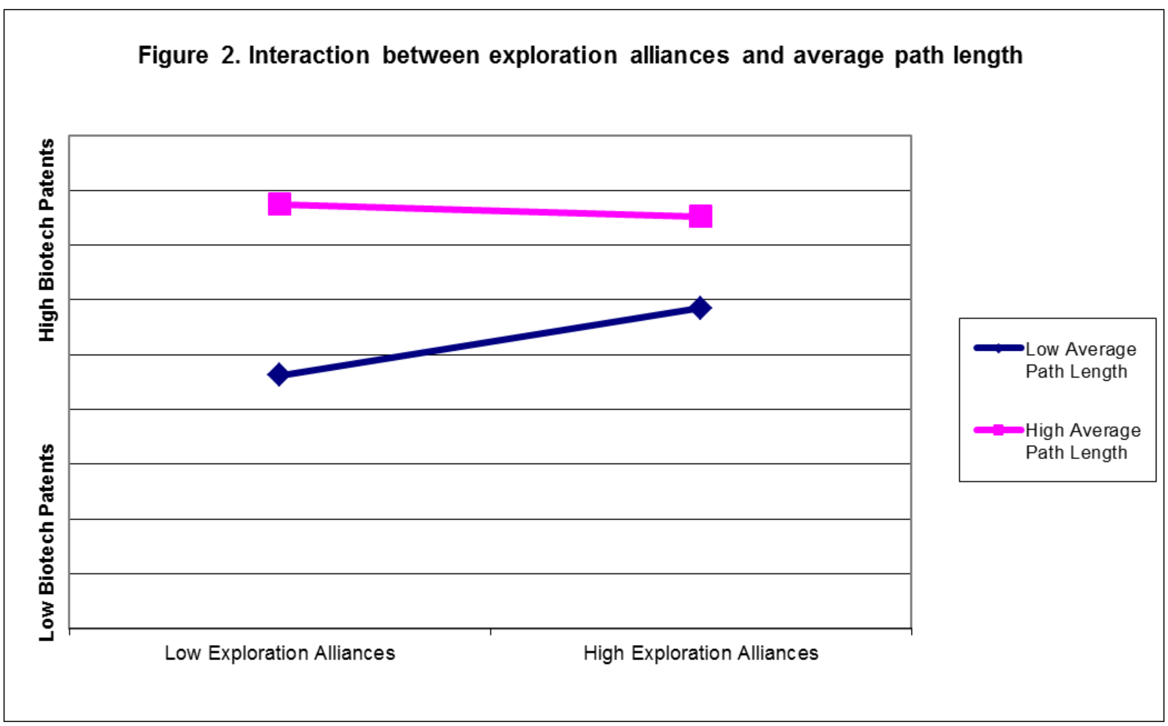

Figure 4.2. Exploration Alliances and Average Path Length

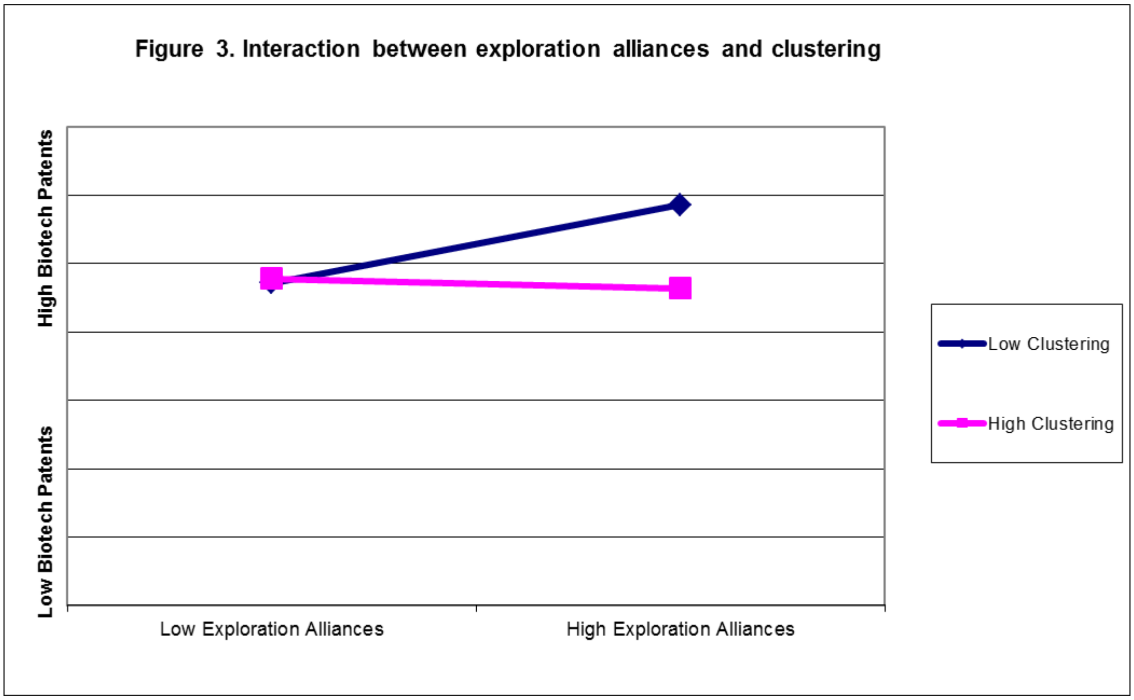

Figure 4.3. Exploration Alliances and Clustering

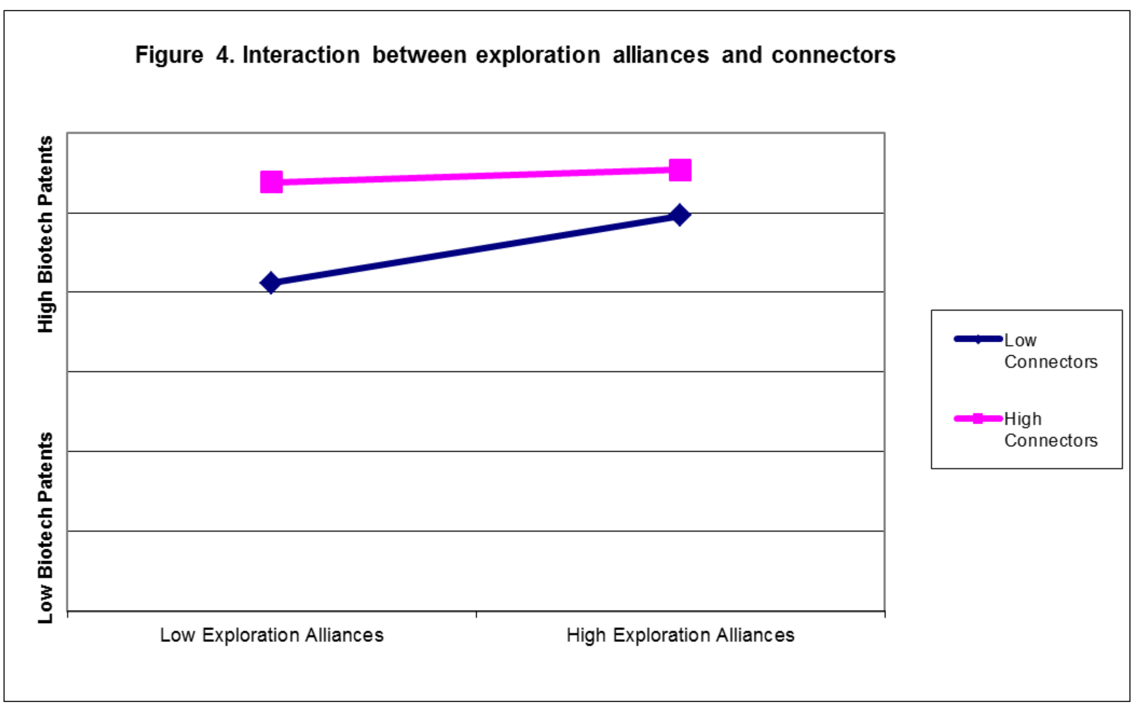

Figure 4.4. Exploration Alliances and Connectors

To provide a more intuitive and clear understanding of these results and uncover additional insights, we display graphically the statistically significant interaction results in Figures 4.1-4.8. Figures 4.1-4.4 are about exploration alliances. We see that exploration alliances are much more effective when coupled with a network that has low recombinatory potential or low coordination costs. Interestingly, the effect from exploration alliances turns negative when coupled with an internal network that has strong recombinatory potential (Figures 4.2-4.3). Figures 4.5-4.8 are about acquisitions. We see that acquisitions are much more effective when coupled with a dense or a broad internal network which needs or can absorb talent infusion (Figures 4.5-4.6). In addition, although acquisitions are indeed less effective when the firm has individuals with recombinatory potential or untapped talent, the effects are small in magnitude (Figures 4.7-4.8). This finding can be explained by the fact that acquisitions, relative to individual roles, have much stronger positive effects on biotech patent output. The strongest and most interesting result from the figures on acquisitions is the one on the interaction between acquisitions and network density: there is a strong substitution effect between the two, in that the effect from acquisitions turns negative for networks of low density (Figure 4.5).

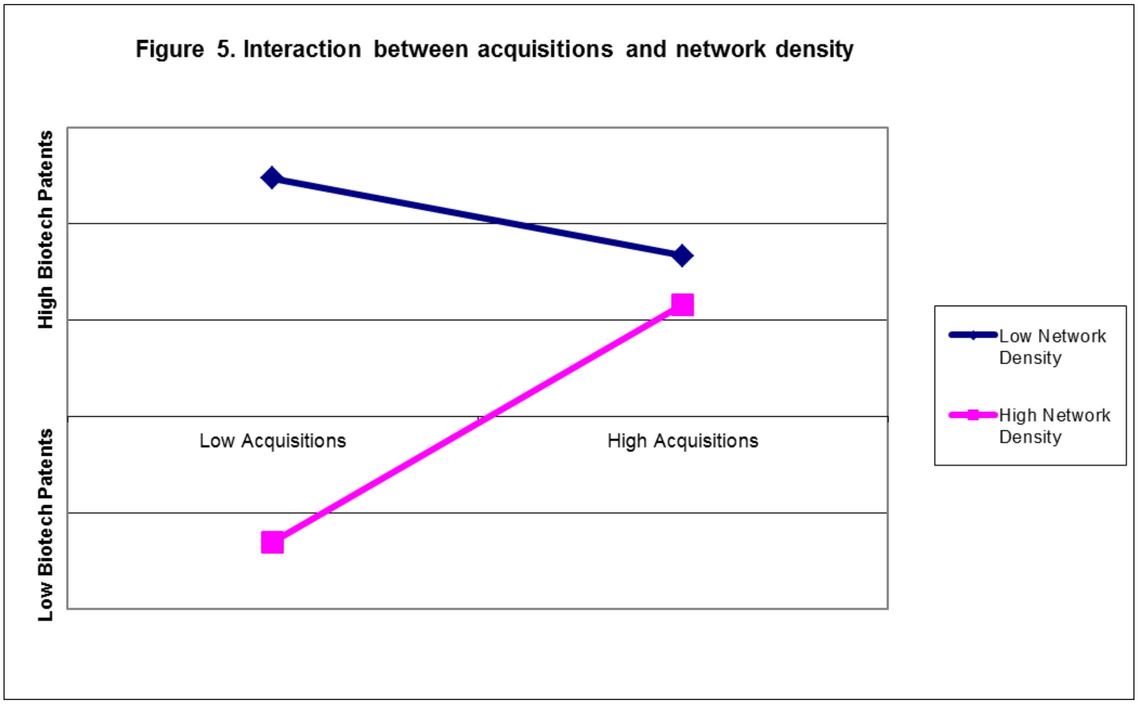

Figure 4.5 Acquisitions and Network Density

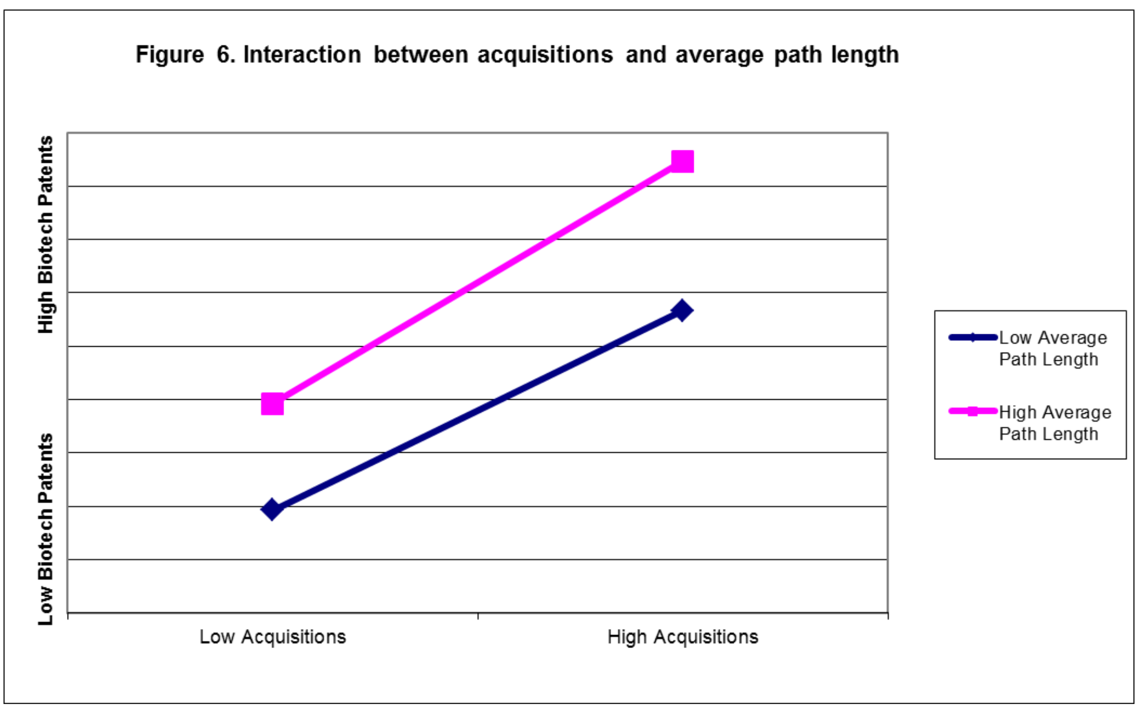

Figure 4.6. Acquisitions and Average Path Length

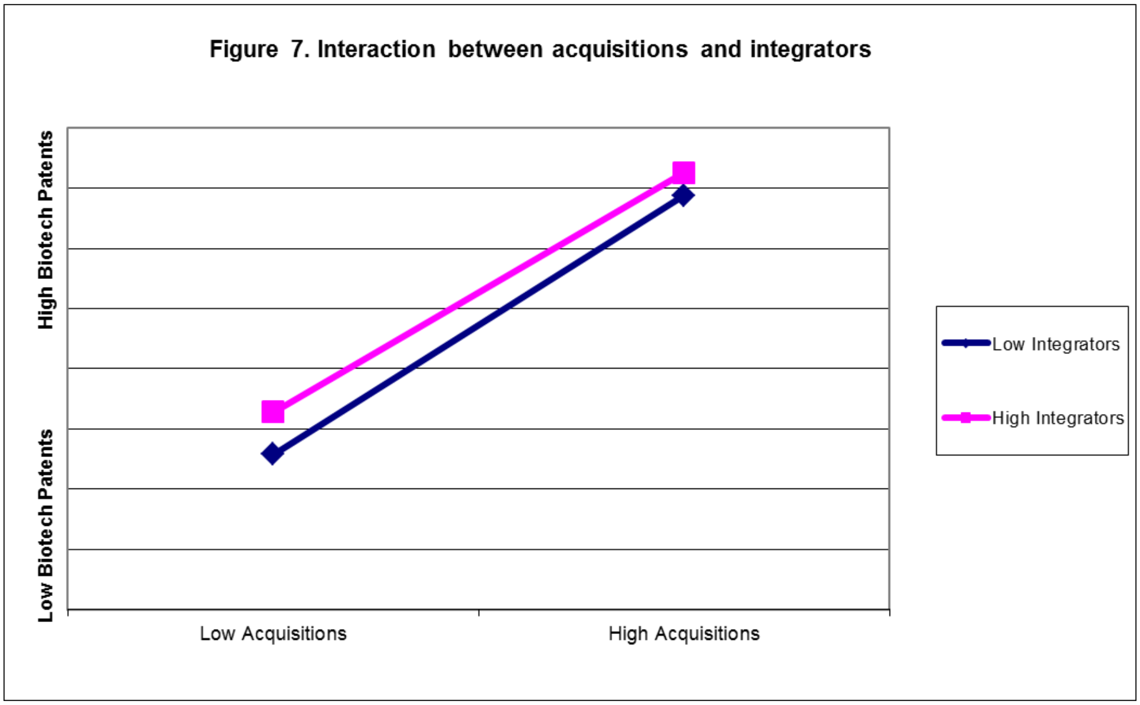

Figure 4.7. Acquisitions and Integrators

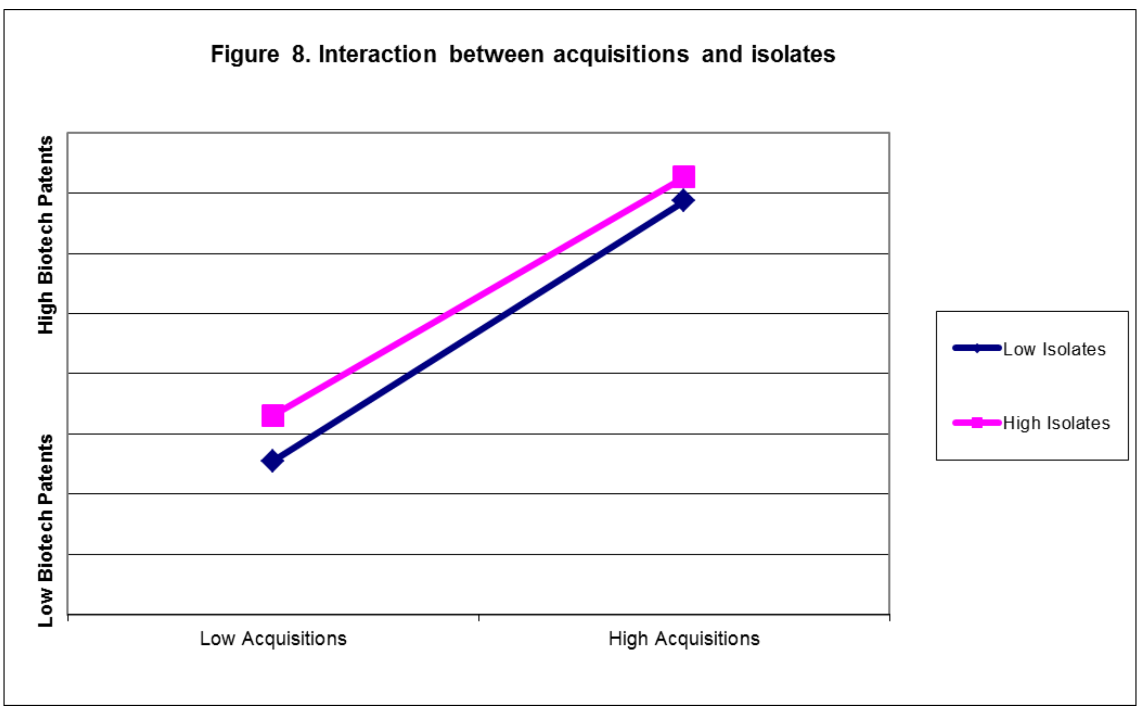

Figure 4.8. Acquisitions and Isolates

4.5. Discussion

Incumbent firms in high tech industries are often faced with competence-destroying technological change. In their effort to adapt and develop capabilities in a new knowledge area, they have several options available to them: internal capability development and a wide array of alternative external knowledge sourcing strategies. In this study, we made an effort to address a critical question: how effective is external knowledge sourcing under different circumstances? In particular, we developed a theory suggesting that the effectiveness of external sourcing partly depends on the state of internal capabilities which incumbents develop as they slowly generate knowledge related to the emerging technological paradigm. More specifically, we argued that if incumbents already possess a strong potential for internal knowledge recombination or a high level of coordination costs in the internal knowledge generation process, then external sourcing will be less effective in delivering the necessary capability building. This argument was developed based on a simple idea: if incumbents can do capability building internally then any external source will simply expand potential knowledge trajectories, thus substituting for knowledge paths suggested by internal development. Similarly, if incumbents already generate knowledge internally and face high coordination costs then any external source will add to the coordination burden and have compensating knowledge producing effects. We applied social network theory to the emerging internal knowledge network of incumbents adapting to a technological discontinuity in order to capture their recombinatory potential and level of coordination costs.

We tested our theoretical framework in the global pharmaceutical industry. Pharmaceutical incumbents were forced to adapt to a changing paradigm with the emergence of biotechnology. To do so, they followed a wide array of capability sourcing strategies, which included internal development, exploration alliances with sources of biotech knowledge, and outright acquisitions of biotech targets. The results provided general support for our theoretical framework. Exploration alliances were indeed less effective as capability building mechanisms when incumbents had internally the potential for knowledge recombination and already faced high coordination costs. Acquisitions were also less effective when coupled with internal human capital characterized by high recombinatory potential or a high level of internal untapped knowledge-producing talent. However, the results also uncovered an interesting divergence between alliances and acquisitions as capability building mechanisms. Instead of losing their effectiveness as suggested by our framework, acquisitions are even more effective when the firm's network needs talent infusion to broaden its knowledge base and escape competence traps or when the firm's network has the necessary breadth to absorb the infusion of talent. This result likely points to a difference in the nature of capability building: while exploration alliances may have long-term knowledge infusion benefits, acquisitions are more likely to result in shorter-term infusion of knowledge-producing human capital.

This study makes two primary contributions. First, we contribute to the literature on the degree of complementarity between external and internal innovation strategies. We move beyond predicting why or when incumbents will choose one or the other. We also move beyond the implementation problem, that is, understanding what can incumbents do to make either one of them more effective, independently. We recognize that incumbent firms are more likely to engage in concurrent sourcing when faced with a radical technological discontinuity and that their ability to select the right sourcing mode is a critical skill that remains underemphasized in the literature. Therefore, we shed light on the selection problem: we make an effort to explain why and show that choosing an external knowledge sourcing strategy may be more or less effective contingent upon the state of the firm's internal capabilities; namely, its recombinatory potential and coordination costs. As a result, we suggest that the degree of complementarity between internal and external capability sourcing also depends on two attributes of the firm's internal capabilities that have been previously neglected.

The second major contribution of this study is the application of social network theory to conceptually and empirically capture the two capability attributes. The two dominant theories of knowledge boundary choice have been criticized for underemphasizing the importance of knowledge production costs and an inability to identify the microfoundations of internal capabilities. Here, we partly address these shortcomings. As incumbent firms slowly develop capabilities in an emerging paradigm, internal knowledge networks of interpersonal collaboration emerge. Analyzing these networks can shed some light on the state of internal capabilities. In particular, by analyzing firm-level knowledge network micro-structures we showed how certain network metrics (e.g. network density, average ties per knowledge stock, average path length, and clustering) can capture the firm's potential for knowledge recombination and internal coordination costs. In addition, we went a step further and we showed how applying network concepts at the individual level of analysis (e.g. ego-network size, density, structural holes, reach, etc.) can also uncover deeper microfoundations of capabilities existing at the individual level of analysis and provide additional insights beyond firm-level averages.

As any study, this one is not without limitations. First, we rely only on alliances and acquisitions as external knowledge sourcing modes. Although these two modes are indeed major levers for capability development, they are not the only ones available to incumbents. Second, we overemphasized the knowledge-sourcing component embedded in these innovation strategies. However, alliances and acquisitions cover many more strategic objectives than simply knowledge sourcing. We made an effort to solve this problem by focusing only on exploration alliances, which have a much stronger knowledge orientation, with sources of biotech knowledge and acquisitions by pharmaceutical incumbents that directly involved biotech firms. Still, even these modes do not simply occur for knowledge development. Nevertheless, we submit that they do consist of strong knowledge flows and therefore, our arguments of knowledge substitution should still hold. Third, we relied on co-patenting events to develop intrafirm knowledge networks. Although patenting is really prevalent in this industry, there are many more sources of internal network formation that our study neglects. Finally, we relied on interpersonal collaboration and the structure of the network to proxy for recombinative potential and coordination costs. Future research can uncover additional ways of capturing these attributes and capture other sources of internal production costs like internal social frictions (Capron and Mitchell, 2009) or social envy and comparison costs (Nickerson and Zenger, 2004).

We conclude with the implications of this study for managers. First, we provide managers with an additional way of evaluating the state of their firm's internal capabilities using social network concepts. Second, we offer theory and evidence on the important role of the firm's internal recombinative potential and coordination costs when it comes to evaluating the effectiveness of external knowledge sourcing strategies. Perhaps more importantly, we show that although external sourcing strategies are generally effective as knowledge-building mechanisms, they are less effective when coupled with an internal capability to generate knowledge or with high internal coordination costs. In this study, we did not have any measures for the costs of external knowledge sourcing modes. However, it is widely documented that both alliances (e.g. knowledge misappropriation, choosing the right partner) and acquisitions (e.g. overpayment, post-acquisition integration) come with a number of challenges for managers of incumbent firms. Therefore, it is critical to know that if an external sourcing mode is chosen for its knowledge benefits and is evaluated vis-à-vis its costs, then its benefits may be overstated when coupled with a solid state of internal knowledge recombination capabilities or high coordination costs.

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CHAPTER 4 APPENDIX

Table 4.1. Descriptive Statistics

Table 1. Descriptive statistics and correlation matrix

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Biotech patents	24.75	28.97																			
2	Merged firm	0.15	0.36	0.36																		
3	EU	0.30	0.46	0.17	0.09																	
4	US	0.34	0.47	0.22	0.17	-0.47																
5	Pharma	0.49	0.50	0.01	0.00	-0.02	-0.06															
6	Overall innovative performance	82.92	105.40	0.56	0.09	0.22	0.19	-0.35														
7	Biotech focus	0.50	0.46	0.10	0.14	0.04	-0.12	0.30	-0.34													
8	Exploration alliance experience	7.37	11.78	0.49	0.42	-0.04	0.19	-0.02	0.16	0.14												
9	Acquisition experience	2.06	6.99	0.36	0.36	-0.02	0.20	0.08	0.11	0.10	0.67											
10	Network size	140.72	132.53	0.80	0.42	0.21	0.06	0.00	0.43	0.12	0.65	0.45										
11	Star inventors	2.93	7.13	0.59	0.34	0.15	0.06	0.01	0.34	0.07	0.43	0.30	0.58									
12	Exploration alliances	0.90	1.81	0.41	0.29	0.02	0.16	0.00	0.15	0.10	0.67	0.42	0.47	0.35								
13	Acquisitions	0.33	1.20	0.34	0.30	0.03	0.14	0.07	0.11	0.10	0.48	0.74	0.38	0.23	0.38							
14	Average ties per patent	9.55	14.86	0.07	0.04	0.01	-0.19	-0.05	-0.02	0.06	0.13	0.08	0.24	0.18	0.07	0.06						
15	Network density	0.06	0.07	-0.38	-0.20	-0.04	-0.23	0.07	-0.30	0.05	-0.25	-0.15	-0.41	-0.18	-0.19	-0.13	0.08					
16	Average path length	2.55	1.21	0.56	0.27	0.07	0.03	0.01	0.26	0.14	0.45	0.34	0.64	0.36	0.32	0.26	0.17	-0.32				
17	Clustering	0.85	0.09	-0.25	0.00	-0.02	-0.31	-0.01	-0.22	0.02	0.01	-0.05	-0.11	-0.14	-0.03	-0.04	0.03	0.20	-0.30			
18	Integrators	5.28	11.44	0.31	0.14	0.11	-0.14	0.00	0.13	0.08	0.24	0.18	0.48	0.46	0.14	0.10	0.46	-0.05	0.29	-0.04		
19	Connectors	5.23	7.31	0.41	0.23	0.12	-0.09	-0.05	0.21	0.12	0.35	0.23	0.50	0.55	0.23	0.17	0.24	-0.18	0.54	-0.19	0.45	
20	Isolates	1.99	6.04	0.30	0.07	0.02	0.22	0.11	0.15	0.06	0.24	0.12	0.33	0.12	0.20	0.09	-0.06	-0.20	-0.03	0.04	-0.07	-0.10

N = 1751 observations

Table 4.2. Fixed-Effects Negative Binomial Regression Predicting Number of Biotech Patents

Variable	Model 1		Model 2		Model 3		Model 4	
Constant	Incl.		Incl.		Incl.		Incl.	
Year Effects	Incl.		Incl.		Incl.		Incl.	
Merged firm	0.056	*	0.056	*	0.079	**	0.072	**
	(0.037)		(0.036)		(0.037)		(0.037)	
EU	-1.304	***	-1.317	***	-1.402	***	-1.351	***
	(0.208)		(0.207)		(0.216)		(0.212)	
US	-1.146	***	-1.048	***	-1.197	***	-1.097	***
	(0.206)		(0.207)		(0.215)		(0.212)	
Pharma	-0.010		0.050		-0.030		0.023	
	(0.130)		(0.133)		(0.131)		(0.134)	
Overall innovative performance	0.003	***	0.003	***	0.003	***	0.003	***
	(0.000)		(0.000)		(0.000)		(0.000)	
Biotech focus	0.269	***	0.290	***	0.275	***	0.293	***
	(0.020)		(0.021)		(0.021)		(0.021)	
Exploration alliance experience	0.003	**	0.006	***	0.004	**	0.006	***
	(0.002)		(0.002)		(0.002)		(0.002)	
Acquisition experience	-0.013	***	-0.012	***	-0.014	***	-0.013	***
	(0.003)		(0.002)		(0.003)		(0.003)	
Network size	0.001	***	0.002	***	0.002	***	0.002	***
	(0.000)		(0.000)		(0.000)		(0.000)	
Star inventors	0.003	*	0.003	*	0.004	**	0.003	*
	(0.002)		(0.002)		(0.002)		(0.002)	
Exploration alliances	-0.006		0.024	*	0.007		0.025	*
	(0.006)		(0.019)		(0.006)		(0.019)	
Acquisitions	-0.008		0.212	***	0.016	*	0.207	***
	(0.009)		(0.049)		(0.011)		(0.050)	
Average ties per patent	-0.099	***	-0.099	***	-0.116	***	-0.110	***
	(0.020)		(0.019)		(0.020)		(0.020)	
Network density	-0.591	***	-0.536	***	-0.592	***	-0.536	***
	(0.071)		(0.068)		(0.070)		(0.069)	
Average path length	0.131	***	0.127	***	0.114	***	0.120	***
	(0.013)		(0.014)		(0.014)		(0.014)	
Clustering	-0.024	**	-0.032	**	-0.022	*	-0.029	**
	(0.014)		(0.015)		(0.014)		(0.015)	
Integrators	0.020	*	0.025	**	0.035	***	0.027	**
	(0.013)		(0.013)		(0.013)		(0.013)	
Connectors	0.035	***	0.031	***	0.051	***	0.046	***
	(0.012)		(0.012)		(0.013)		(0.013)	
Isolates	0.022	**	0.010		0.038	***	0.029	**
	(0.010)		(0.011)		(0.016)		(0.015)	

Table 4.2 continued

Exploration alliances X		-0.027***		-0.022*
Average ties per patent		(0.010)		(0.014)
Exploration alliances X		0.014		-0.006
Network density		(0.058)		(0.061)
Exploration alliances X		-0.036***		-0.036***
Average path length		(0.009)		(0.009)
Exploration alliances X		-0.031**		-0.032**
Clustering		(0.016)		(0.018)
Exploration alliances X			0.003	0.010
Integrators			(0.007)	(0.008)
Exploration alliances X			-0.021***	-0.017***
Connectors			(0.006)	(0.006)
Exploration alliances X			-0.004	-0.004
Isolates			(0.003)	(0.004)
Acquisitions X		-0.016**		-0.005
Average ties per patent		(0.007)		(0.011)
Acquisitions X		0.446***		0.409***
Network density		(0.097)		(0.101)
Acquisitions X		0.022***		0.020***
Average path length		(0.008)		(0.008)
Acquisitions X		0.013		0.017
Clustering		(0.019)		(0.022)
Acquisitions X			-0.012***	-0.008**
Integrators			(0.004)	(0.005)
Acquisitions X			0.004	0.002
Connectors			(0.005)	(0.006)
Acquisitions X			-0.014***	-0.009**
Isolates			(0.005)	(0.005)
No. of observations / groups	1751 / 96	1751 / 96	1751 / 96	1751 / 96
Chi square	2583.41	2778.88	2652.74	2792.98
Δ chi square		195.47***	69.33***	209.57***

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01; standard errors in parentheses

CHAPTER 5
CONCLUSION

In this dissertation, I have attempted to highlight the important role of certain individuals as drivers of firm-level innovative outcomes. However, in contrast to extensive existing work that focuses on the highly productive (i.e. star) knowledge workers of an organization, I examine the importance of another set of individuals: actors who using their productive and collaborative behavior end up occupying a position in their firm's network that makes them consequential for a number of innovation-related outcomes. They do so not because of their productivity but because of their critical network position and the capacity for knowledge recombination that results from their collaborative behavior. I rely on the knowledge base view as the conceptual lens to explain how new knowledge is generated within organizations. I use network theory and findings from innovation research to identify individuals and firm-level network structures that drive a number of innovation-related firm-level outcomes. As a result, the main contribution of this dissertation is to highlight a number of relatively neglected factors at the micro level of analysis which can improve relevant firm-level performance variables: the capacity of an organization to generate new knowledge, the capacity of an organization to generate radically new knowledge while incrementally improving existing knowledge stocks, and the capacity of an organization to choose the appropriate knowledge sourcing mechanisms when dealing with adaptation to a changing technological paradigm.

In more detail, in the first chapter I show that relational stars are positively associated with their firm's quantity and quality of inventive output. Relational stars include integrators and connectors. Integrators source knowledge from many different actors because they have extensive collaborative networks and connectors source dissimilar stocks of knowledge because they collaborate across knowledge clusters and span structural holes in their firms' knowledge networks. On the other hand, I show that it is the isolated knowledge producers and the star knowledge workers who are positively associated with the productivity of their firm's inventive output. I argue that this effect is because of their capacity to generate knowledge without having to incur the costs of coordination and collaboration.

In the second chapter, I show that relational stars are positively associated with their organization's capacity to generate radically new knowledge stocks, knowledge that is quite different from the existing knowledge base (i.e. exploratory output). In addition, isolated actors are quite good at incrementally improving existing knowledge (i.e. exploitative output). More importantly, I find that organizations which want to be able to do both effectively (i.e. ambidextrous output) should focus on the certain group of individuals who are good at both exploration and exploitation and on retaining a certain level of connectedness between their exploratory and exploitative activities.

In their third chapter, I show that the effectiveness of external knowledge sourcing mechanisms that firms use to adapt to a changing technological paradigm depends on the current state of internal capabilities and in particular, on the capacity of the firm's network to recombine knowledge in the future and on the level of coordination costs currently in the network. To proxy for these two factors, I also rely on relational stars and firm-level network structures. I find that external knowledge sourcing is less effective when combined with an internal network that is capable of knowledge recombination or already has a high level of coordination costs.

Overall, I attempt to discover the type of individuals that are positive drivers of a firm's performance in generating new knowledge, learning different types of knowledge, and adapting to a changing knowledge space. I find that the simple focus on highly productive knowledge workers may be incomplete. Innovation is a team-based endeavor which relies on knowledge sharing, transfer, recombination, and reconfiguration of existing knowledge stocks. Individuals with the relational capacity to effectively implement these processes are at least as important as star knowledge workers for the performance of the system as a whole. The same holds for the overall structure of a firm's knowledge network. Both of these factors are variables that are at least partly under the control of the management team and therefore, I provide here a set of ideas directed at managers on how to identify individuals and design knowledge structures internally to make their organizations more innovative.