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ONE FOOT IN, ONE FOOT OUT: HOW DOES INDIVIDUALS' EXTERNAL SEARCH BREADTH AFFECT INNOVATION OUTCOMES?

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The "variance hypothesis" predicts that external search breadth leads to innovation outcomes, but people have limited attention for search and cultivating breadth consumes attention. How does individuals' search breadth affect innovation outcomes? How does individuals' allocation of attention affect the efficacy of search breadth? We matched survey data with complete patent records, to examine the search behaviors of elite boundary spanners at IBM. Surprisingly, individuals who allocated attention to people inside the firm were more innovative. Individuals with high external search breadth were more innovative only when they allocated more attention to those sources. Our research identifies limits to the "variance hypothesis" and reveals two successful approaches to innovation search: "cosmopolitans" who cultivate and attend to external people and "locals" who draw upon internal people. © 2014 The Authors. *Strategic Management Journal* published by John Wiley & Sons Ltd.

INTRODUCTION

Most theories of innovation search recognize that the breadth of external search is important to identifying new ideas (Gibbons and Johnston, 1974; von Hippel, 1988; Jeppesen and Lakhani, 2010; Laursen and Salter, 2006; Leiponen and Helfat, 2011; March, 1991). The "variance hypothesis" predicts that exposure to diverse sources of information (e.g., Owen-Smith and Powell, 2004; Powell, Koput, and Smith-Doerr, 1996) provides the "requisite variety" of ideas and knowledge needed to create innovations. The breadth of external search also helps increase the likelihood of a successful payoff given the risk and uncertainty associated with innovation endeavors (Leiponen and Helfat, 2011). What is less recognized is that cultivating a broad external search has an opportunity cost as it takes attention away from other activities internal to the firm.

Individuals who span organizational boundaries (Allen, 1977) to search for new innovations must decide how to allocate their attention across multiple search sources. The boundary-spanning literature has a long history investigating the types of individuals likely to form ties that span organizational boundaries (Tushman and Scanlan, 1981) and their effects on team (Ancona and Caldwell, 1992; Marrone, Tesluk, and Carson, 2007) and organizational performance (Dollinger, 1984). But this research does not tend to acknowledge that those

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who bridge boundaries in the search for innovative ideas do so at the expense of other activities. While the variance hypothesis has robust support at firm, team, and individual levels, few theories of innovation have accounted for the time needed to cultivate a broad external search and how this may affect innovation outcomes. Thus, our research examines exactly this question: How does individuals' search breadth affect innovation outcomes? How does individuals' allocation of attention affect the efficacy of search breadth?

At the firm level, variance in search sources hedges risk. Firms can manage the allocation of attention between internal and external search sources by cultivating a portfolio of different initiatives that pursue search strategies with different risk profiles. "By accessing a greater number of knowledge sources, the firm improves the probability of obtaining knowledge that will lead to a valuable outcome" (Leiponen and Helfat, 2011: 225). Thus, organizations rarely conduct one monolithic approach to innovation search but, rather, pursue a distributed approach, allocating individuals to explore various domains. The task of searching for new ideas is inherently a human one: organizations cannot themselves "search" (Li *et al.,* 2013)—although a firm's leadership and strategic direction can set the search agenda. The actual conduct of a successful search for innovations depends "on the individuals who stand at the interface of … the firm and the external environment" (Cohen and Levinthal, 1990: 132).

Yet, the search patterns of individuals are not well understood (Gruber, Harhoff, and Hoisl, 2013; Maggitti, Smith, and Katila, 2013; Salter *et al.,* forthcoming), and this has consequences for the assumptions theorists make about how innovation search accumulates at the organizational level. Individuals live within the same 24-hour day and cannot, like a firm, hedge against the risk embedded in many different search strategies to achieve innovative results. To innovate effectively, individuals need to figure out how to allocate their attention to a variety of external information sources while still focusing on the internal needs of the organization so that ideas sourced externally will have relevance for the firm. Thus, at the individual level, "attention should play an important role in the search for and development of innovative ideas" (Koput, 1997: 533).

Attention-based theories of the firm recognize that the attention of both individuals and organizations is a scarce resource and that any allocation of attention has an opportunity cost (Ocasio, 1997, 2011). Attending to information sources inside the firm takes away from ideas outside the firm and vice versa. Thus, we suspect that the attention individuals give to search breadth affects the efficacy of their search. Attention-based theories typically focus on how leaders influence or direct the attention of organization members (Li *et al.,* 2013). How individuals allocate their attention among search sources and how this affects innovation outcomes has not been explored. This is a critical research gap because in dynamic and competitive environments (e.g., Martin and Eisenhardt, 2010) centralized search is not likely to be effective (Cohen and Levinthal, 1990). Search is more likely to be conducted by individuals straddling the firm and its environment (e.g., Dokko and Rosenkopf, 2010; Lavie and Rosenkopf, 2006). Although theorists like to talk about "innovation landscapes" or "terrains," Maggitti *et al.'s* (2013) in-depth exploration of individual inventors did not find these metaphors relevant to individuals' search processes. Rather, inventors emphasized "information comprehensiveness and acquisition of up-to-date knowledge as on-going"—a challenge to maintain for anyone hoping to create something novel.

Thus, our question as to how individuals' allocation of attention to different information sources affects innovation search is central to understanding how individuals navigate the innovation search process, which ultimately accumulates at the firm level. What is needed is empirical research on how individuals engaged in innovation search allocate their finite attention and how this affects their ability to manage search breadth. Thus, we examined how individuals in key innovative search roles drew upon internal and external sources of information, how this affected their ability to leverage search breadth, and how divergent search patterns affected the quantity, novelty, and quality of patents. Doing so contributes a more nuanced understanding of the search process at the level where search is conducted and also provides theoretical and empirical traction as to how individual search behavior varies in its effect on innovation outcomes.

THE VARIANCE HYPOTHESIS

The variance hypothesis: the belief that greater exposure to diverse information sources leads to

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more innovative outcomes has relevance at firm, team, and individual levels, and we consider each in turn.

Firm

Firms diversify their search strategy and portfolio to hedge against the inevitable risk associated with innovation search (Leiponen and Helfat, 2011). While breadth in a firm's innovation objectives is important, breadth in information sources is most associated with a high rate of successful innovations (Leiponen and Helfat, 2011). An increase in the breadth of a firm's search strategy "add[s] new elements to the set, improving the possibilities for finding a useful combination" (Katila and Ahuja, 2002: 1185). Thus, breadth not only hedges risk, but also enriches the pool of solutions available to solve innovation challenges endemic to the firm. This logic is core to the argument behind open innovation in terms of the external sourcing of ideas to the firm (Chesbrough, 2003; Dahlander and Gann, 2010). An early study of the use of scientific knowledge in industrial innovations found that over a third of the knowledge in innovations critical to the firm came from external sources (Gibbons and Johnston, 1974). More recently, firms like Procter & Gamble have set targets for the external sourcing of ideas—aiming to secure 50 percent of the ideas for novel products from outside the firm and allocating innovation scouts to realize that goal (Huston and Sakkab, 2006). A broad external search is viewed as vital to the sourcing of innovative ideas that P&G can bring to market to foster organic growth for the firm.

At the firm level, broad external networks benefit firms' growth and performance (Owen-Smith and Powell, 2004; Powell *et al.,* 1996). The greater the breadth of partners firms interact with, the greater the innovation outcomes (Laursen and Salter, 2006). External partners can be considered a type of search channel that provides different sources of information but also requires different norms of exchange. Thus, cultivating external search breadth across multiple types of partners takes significant effort. Laursen and Salter (2006: 133) suggest that "the concept of search channels shifts attention toward the type and number of pathways of exchange between a firm and its environment rather than toward the degree of its interaction within each of these search channels. In doing so, it focuses attention on the variety of channels used by the firm in its search activities." We would argue that the concept of search channels should also draw attention to the human resources needed to cultivate those channels. Typically, it is individuals who will be responsible for developing and managing external search channels in order to extract value for the firm.

Team

At the team level, exploration of the variance hypothesis tends to examine either the composition of the team or the diversity of search sources explored by the team. Teams with greater diversity in member composition experience higher rates of productivity (Reagans and Zuckerman, 2001), creativity, and innovation (Austin, 1997; Bantel and Jackson, 1989; McLeod, Lobel, and Cox, 1996). Variance in scientific and technical teams' expertise enhances innovation outcomes (Singh and Fleming, 2010) and contributes to higher rates of innovation breakthroughs (Fleming, Mingo, and Chen, 2007; Hargadon, 2005). In addition to team composition, the breadth of external networks matters. Ruef (2002) found that entrepreneurial teams embedded in heterogeneous networks were more likely to attempt innovation (as measured by patent and trademark applications) than entrepreneurial teams in more homogenous networks. Top management teams who pursued a more diverse set of search sources were more likely to introduce novel products (Li *et al.,* 2013). While both approaches examine how a team's access to a breadth of information affects innovation outcomes, it is the diversity of information sources accessed rather than team composition that may be relevant to innovation search at the individual level.

Individual

The notion that individuals exposed to broad external networks will inherit greater knowledge and facility in both accumulating and taking advantage of new knowledge is not new and extends from early work by Gouldner (1957). Gouldner theorized that, while "locals" demonstrated commitment and loyalty by orienting themselves to affairs internal to the organization, "cosmopolitans" oriented to diverse professional networks outside the organization benefited from the expertise generated from their external ties. Gouldner argued that, as a result, "experts" would have greater opportunities for job mobility and be less "committed to their employing organization than to their specialty" (1957: 288). While Gouldner did not theorize about external search breadth per se, he did find that individuals with a cosmopolitan orientation were more likely to get intellectual stimulation from sources outside the organization (1957: 296), which could produce a broad external network.

When it comes to innovation, prior research shows that engineers and scientists who have access to diverse domains of expertise are better able to apply solutions developed for one domain to a new domain (Fleming, 2001; Gruber *et al.,* 2013; Hargadon and Sutton, 1997; Singh and Fleming, 2010), enhancing the efficiency of innovation search. Individuals who bridge heterogeneous groups of people gain access to unique information resulting in a "vision advantage" (Burt, 2004: 359). This vision advantage is also perceived by other members—Menon and Pfeffer (2003) found that external sources of information were more valued by other organizational members as they were perceived to be more rare than internal sources of information. Thus, individuals who develop external search breadth are more likely to access divergent sources of knowledge that can expand the population of ideas available to solve innovation challenges inside the firm (Fleming and Sorenson, 2001; Nelson and Winter, 1982; Reagans and Zuckerman, 2008; Rosenkopf and Nerkar, 2001; Salter *et al.*, forthcoming).

Benefits that stem from connecting disparate knowledge resources in novel ways are limited when individuals search within their own organization (Dearborn and Simon, 1958). Search strategies that do not extend outside the firm boundary are less likely to have impact on subsequent technological evolution (Rosenkopf and Nerkar, 2001). Maggitti and colleagues' examination of inventor's search and discovery process found that "it is not always the depth of knowledge and experience of the searcher that results in discovery. Rather, it is the *unique breadth* of these components in addition to the ability to draw from seemingly different terrains and categories to arrive at solutions and discoveries" (2013: 97, emphasis added). Jeppesen and Lakhani's research on the innovation platform InnoCentive 2010 shows that people who were distant from the knowledge domain where innovation challenges originated were more likely to find solutions to those problems than those closest to the relevant knowledge domain. The question is, given the finite amount of time that individuals possess, how much search breadth can individuals cultivate before the benefits from search dissipate? How do individuals cultivating external search breadth balance their attention to external search with attention to the innovation needs of the firm? What is missing is an understanding of how the opportunity costs invoked by the variance hypothesis affect innovation outcomes at the level of analysis where search occurs: individuals.

EXPLORING THE LIMITS OF THE VARIANCE HYPTOHESIS

At the firm level, there are diminishing returns to external search breadth (Laursen and Salter, 2006; Leiponen and Helfat, 2011). Too much attention to searching different external knowledge sources can, at some point, be detrimental (Koput, 1997: 528) as firms have a limited absorptive capacity (Cohen and Levinthal, 1990). Excess external search can lead to wasted resources when firms gather more information than they can use, producing more knowledge than can be integrated with existing capabilities (Cyert and March, 1963; Hansen and Haas, 2001). As external search breadth increases, "the proportion of new knowledge to be integrated into a firm's knowledge base increases [and] so do the technological and organizational challenges in integration" (Katila and Ahuja, 2002: 1185). In this scenario, the costs of integration exceed the benefits of search breadth. More information is created than can be screened, processed, or acted upon: a wealth of information creates a poverty of attention (Simon, 1997: 40).

If this is the case, then diminishing returns to external search breadth may be even more relevant for individuals as they cannot scale themselves as well as firms and face finite search time. Innovation scholars often neglect what is central for attention-based scholars—all types of search incur an opportunity cost. Cultivating external search breadth can come at the expense of time needed to understand how external knowledge can be integrated with the firm. Drawing on Simon's (1997) observations of how individuals and organizations experience limits in processing information, the attention-based view of the firm (Ocasio, 1997, 2011) views management's task as directing people's attention to the core challenges of the firm. From Ocasio's perspective, how people direct their attention is a critical precursor to action: it affects

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the information people will be exposed to and thus the nature of solutions people bring to bear to address the firm's challenges. Thus, how people allocate their attention is critical to understanding how individual behavior affects organizational behavior.

The importance of internal search sources

When it comes to the search for innovations, if people simply attend to external information sources, they may acquire novel ideas but have a difficult time understanding the firm's innovation challenges and lack the social capital needed to have ideas that are sourced externally accepted and integrated within the firm (e.g., Burt, 2004; Fleming *et al.,* 2007; Obstfeld, 2005). Attention to internal information sources is critical to identifying opportunities to apply ideas gathered from external sources to the firm's innovation challenges (e.g., Fleming *et al.,* 2007; Obstfeld, 2005). Ideas from external sources often do not transfer well and can be difficult to integrate with a firm's existing activities (Hansen, 1999, 2002). Without engaging with internal collaborators to translate (Bechky, 2003; Carlile, 2004) or persuade colleagues of the value of external ideas (e.g., Dutton *et al.,* 2001; Howard-Grenville, 2007), ideas from external sources can face rejection (Katz and Allen, 1982).

On the other hand, if people devote all their attention to internal sources of information, they may limit the variance in ideas to which they are exposed and fail to introduce novel ideas to the firm, inhibiting innovation. Knowledge from both internal and external sources is needed to produce novel innovations (Fabrizio, 2009; Gibbons and Johnston, 1974), but too much attention to internal information sources may limit the number and range of novel ideas introduced. As a result, Allen (1977) suggests that individuals need to be "communication stars" excelling at maintaining external and internal information sources to both cultivate variety and develop credibility when introducing ideas from outside the firm. Yet, doing both equally well can be tricky.

The effects of attention on search breadth

Consider that, as an individual's external network becomes broader, several choices with respect to allocating attention unfold. If an individual allocates the same amount of time per person, the total time spent across the network will grow in alignment with the network's growth. This may not be a sustainable equilibrium given the need to also attend to internal search sources. An alternative is that people devote a specified amount of time to external networking and, as the breadth of the network grows, the time devoted to each person is reduced. The danger of the latter scenario is that individuals with high external search breadth who don't allocate much time to each external person risk creating "weak" or superficial ties (Carlile, 2004; Hansen, 1999) that may not be rich enough to allow the depth of knowledge transfer needed to create novel innovations. While weak ties are good for some types of information transfer—such as getting a job (Granovetter, 1973), they are not always effective at transferring complex information (Hansen, 1999). Thus, people who cultivate broad external networks may need to spend significant time with their external information sources to learn how the ideas produced in one domain can be reused in novel domains (e.g., Hansen, 1999; Murray and O'Mahony, 2007).

How individuals allocate their attention to internal and external search sources may thus affect the degree to which benefits can be extracted from external search breadth. Individuals who develop external search breadth without increasing the time devoted to those ties may not gain enough knowledge to make use of those information sources. In other words, unless individuals spend adequate time with the broad search networks they cultivate, the costs of developing external networks may outweigh the benefits. To explore the limits of the variance hypothesis, with full consideration for individuals' finite attention, we examined how scientific and technical professionals in key innovation search roles allocated their attention to internal and external information sources, how much external search breadth they cultivated, and the effects their search behavior had on innovation outcomes.

RESEARCH CONTEXT

We situate our study within IBM, a large global technology and services business with a population of elite experts dedicated to innovation search. We composed a theoretical rather than representative sample (Eisenhardt and Graebner, 2007) of professionals who are boundary spanners and tasked with innovation search who had been granted a great deal of autonomy over their time (see, e.g., Allen, 1977).

"Theoretical sampling simply means that cases are selected because they are particularly suitable for illuminating and extending relationships and logic among constructs" (Eisenhardt and Graebner, 2007: 27). To assess how individuals allocate their attention and how this moderates search breadth, the research sample should meet two criteria: (1) the sample should be tasked with innovation search and have autonomy as to how to conduct that search, and (2) the sample should enable one to trace how different allocations of attention affect search breadth and individual innovation outcomes at a later stage. Our sample meets both criteria but is nonetheless a very specific case, and our findings are limited to firms of similar size and scope.

IBM employs more than 400,000 people and more than half hold scientific or technical qualifications. IBM has a strong tradition of developing innovations inside the organization by establishing technical leadership (Chesbrough, 2003). For example, IBM holds more patents from the U.S. Patent and Trademark Office than any other organization and, for 19 consecutive years, has been the most active patenting organization in the United States. More recently, IBM has developed an array of initiatives to enhance collaboration with external parties to develop novel innovations (Baldwin, O'Mahony, and Quinn, 2003). In these efforts, IBM's leading technical experts and scientists scan the external environment for novel ideas that the firm can leverage and apply.

As noted by Gambardella, Panico, and Valentini (2013), firms often motivate knowledge workers by offering them increased autonomy and learning opportunities. In this regard, autonomous search roles are the reward. At IBM, this happens in two ways. High-performing, senior technical experts can be recognized with two roles: as members of IBM's Distinguished Engineers and as members of the IBM Academy of Technology. Scientists and engineers within IBM are promoted to Distinguished Engineers only when they achieve a solid record of technical innovation excellence.

> *Individuals elevated to the title of IBM Distinguished Engineer must achieve a sustained record of invention, garnering recognition across IBM and the industry for insight and technical expertise. Those honoured possess either a broad competency across multiple areas or a deep technical knowledge in one specific area.*

Promotion to a Distinguished Engineer is a great honor available only to the most talented technical employees, a position they hold for the rest of their careers. Rather than take on managerial responsibilities, they are rewarded with autonomy to search for new ideas that may be of importance to IBM (e.g., Allen and Katz, 1986; Gambardella *et al.,* 2013). Distinguished Engineers are technical role models whose primary responsibility is to inject the organization with novel ideas rather than to manage product teams or have direct operating responsibility.

Members of the IBM Academy are nominated and elected by their peers. The IBM Academy, established in 1989, was modeled on the U.S. Academies of Science and Engineering. Like Distinguished Engineers, individuals are appointed based on their technical accomplishments and are among IBM's top technical people. Academy members are responsible for promoting IBM's technical growth and innovation. IBM promotes about 30 new members annually to spur creative ideas while older members move on to "emeritus status." Although there is no member maximum, the Academy usually consists of about 300 individuals who "identify and pursue technical developments and opportunities relevant to IBM's business, seeking to improve IBM's technical base and its application in successful products, solutions, and services." (Source: internal material). As one Academy of Technology member explained: "Our job is to figure out what the next [thing] is, to sift [through] all the possible things, which ones are going to matter to IBM, and then go and figure out what is really happening and come back with recommendations … why we think this matters, how we think this is going to play out, and where IBM should fit in."

Both Distinguished Engineers and Academy members are granted significant autonomy as to how they search and spend their time, but may seek managerial approval as to the broad technical domains in which they search. For these elites, innovation search is an ongoing dynamic activity: "As far as I am concerned [this technology] isn't the next thing any more. It is here. Whereas [this other technology] really is the next thing right now. A year from now it will be something else." Thus, this population provides an excellent opportunity to examine how individuals' search behavior affects innovation outcomes.

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METHODS

With the permission of the Vice President of Technical Strategy for IBM, we derived a list of all 460 Distinguished Engineers and 317 IBM Academy members in 2008. One hundred and sixty-two individuals were both a Distinguished Engineer and an Academy member, resulting in a population of 615 individuals. We surveyed both cohorts as both are promoted to their roles based on their innovation track record, and both have the autonomy to conduct independent innovation search. As the selection mechanisms differ between Distinguished Engineers and Academy members, we control for this in our analyses.

Data collection

We adopted a multimethod approach combining semi-structured interviews with senior individuals at IBM and two half-day workshops with eight Distinguished Engineers and Academy members to create a survey that would make sense to them. Respondents were linked to a web page where they could fill in the survey on one of our servers. In addition, we retrieved the full U.S. patent records from all 615 individuals in our population. We combined self-reported data from the survey with patent data on innovation outcomes.

Workshops

We organized two workshops to understand our research context and refine the survey instrument. The questionnaire was discussed with Distinguished Engineers and Academy members to gain validity by making sure that we used their language. Based on the interviews and workshops, we revised the questions included in the questionnaire. We pre-tested the questionnaire with workshop participants and modified the survey instrument.

Survey

We distributed the survey to the 615 individuals in the population during the second week of February 2008 and kept the survey live for two weeks. Following Dillman's (2000) proposal, we adopted different tactics to increase the response rate. We started with questions deemed the easiest to respond based on feedback from workshop participants. Effort was placed on the graphical design of the survey, to make it attractive to complete (Dillman, 2000). The survey was accompanied by an e-mail from the Vice President of Technical Strategy in IBM and a member of the Board of Governors of the IBM Academy of Technology, highlighting the importance of the survey to IBM and indicating that the survey was approved by the IBM Employee Survey Review. After distributing two reminders, we reached an effective response rate of 53.7 percent. This is a good response rate given the time constraints of our senior high-level respondents. We tested for response bias by comparing early respondents with late respondents, as studies have shown that late respondents resemble many characteristics of nonrespondents. We compared individuals who responded immediately after we sent the survey with individuals who responded after the second reminder. Simple *t*-tests of the dependent and independent variables did not indicate any significant differences.

Patent records

We supplemented the survey data with full patent records for all 615 individuals in the population for individuals' complete career history. Using Thomson's Delphion database, we downloaded all U.S. patents in the U.S. Patent and Trademark Office (USPTO). With patent information from all 615 individuals in our population, we assessed whether there was any selection bias by comparing the patent rate of individuals who completed the survey with those who did not. One could expect more innovative individuals to have a stronger interest in participating in the survey, which would not constitute a random sample. Respondents had, on average, 1.97 patents post-survey while nonrespondents had 1.98 patents. A *t*-test for difference of means across the two groups confirmed that this was not statistically significant. These analyses led us to conclude that our sample was representative of the target population. Together, the 615 individuals in our population were awarded more than 10,000 patents over our study period. This is a remarkable number, and one survey respondent is among the top 10 most prolific inventors in the USPTO database over the last 10 years.

This extensive data collection effort avoids the common-method bias of using only survey data (Podsakoff *et al.,* 2003: 885). Following Podsakoff *et al.*'s (2003) argument, we adopted procedural and statistical remedies to cope with the potential threat of common-method bias. Different data sources

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for the dependent and independent variables overcome part of the problem. We also protected anonymity, counterbalanced question order, used different question anchors, and varied the scales. To test statistically for common-method bias, we used Harman's (1976) single factor test, which included all the survey items used in the paper in one factor analysis. As no single factor emerged that accounted for a large proportion of the total variance, our research does not appear to suffer from common-method bias.

Variables and measures

While our dependent variables come from the USPTO database between 2001 and 2013, our independent variables come from the survey informed by workshops with IBM in 2008.

Dependent variables

IBM has a strong culture of patenting behavior and emphasizes patent protection as a key factor in their appropriability strategy, consistently holding more patents than any other firm in the USPTO, which generate more than US$1 billion annually in license revenue. Not every great idea will be patented—IBM supports open source software efforts and often makes technical disclosures in the public domain. However, all IBM employees are awarded a monetary sum when they file a patent. For patents with over five inventors, patenting teams share a pooled award. These awards are in place for all IBM employees and do not change for Distinguished Engineers or Academy members. Like Nerkar and Paruchuri (2005), we analyze patents awarded within a single firm, which allows for examination of how individual achievements accumulate at the firm level. Patents are produced by specific individuals and individuals are rewarded for them, but patent assets are owned by the firm.

Our dependent variable is an individual's total number of *patents* granted inversely weighted by the number of inventors on the patent. For instance, a patent with two inventors counts as half for each individual. We sum the cumulative number of weighted patents *post*-survey for each individual, while controlling for a lagged cumulative dependent variable *pre*-survey. Thus, our analyses include a lagged cumulative dependent variable with individuals' patents between 2001 and 2007. A lagged dependent variable can be considered analogous to a fixed effect that accounts for unobserved heterogeneity such as inherent abilities in producing patents (Blundell, Griffith, and Windmeijer, 2002).

We conducted two robustness checks that capture different types of patent outcomes. First, we developed a second dependent variable: the number of *novel patents* inversely weighted by the number of inventors. Here, we account for the novelty of each inventor's patents using the approach developed by Fleming *et al.* (2007). Fleming and colleagues used patent classes to identify whether a patent included previously uncombined patent subclasses. Using this logic, patents that use subclasses that have not been previously combined create a new technological path for the organization. A patent has $n(n-1)/2$ possible combinations where n is the number of patent classes. We count the patent as novel if a patent combines at least one pair of patent classes new to IBM.

As a second robustness check, we constructed a third dependent variable to assess whether our results were affected by the quality of patents produced. We measured an individual's *quality-adjusted patents* by measuring each patent's yearly forward citations inversely weighted by the number of inventors. Forward citations have been argued to be a good proxy for the quality of patents as measured by their impact on other patents (Trajtenberg, 1990). An individual has higher quality patents the more the patents they invent are cited by other patents.[1] With this measure, we can account for the fact that some people may have produced fewer patents but produced patents of higher quality. As expected, the three dependent variables were correlated and the results similar across the different dependent variables. For the purposes of this paper, we report results for the quantity of patents as our primary dependent variable. We run robustness checks using *novel patents* and *quality-adjusted* patents.

Independent variables

Our independent variables were captured in our pretested survey of Distinguished Engineers and Academy members administered in early 2008 as well as additional sources explained below. A summary of all variables, their definitions, and data sources are found in Table S1 in Appendix S1.

[1] Our patent data ends in 2011, and our citation data to patents ends in 2012.

External search breadth. Studies of how firms search for new ideas typically examine a firm's engagement with different types of partners (Laursen and Salter, 2006; Powell *et al.,* 1996) or information sources (Leiponen and Helfat, 2010) as a measure of the breadth of their innovation search. Koput refers to "sources of ideas and information such as competitors, suppliers, trade associations, universities, and others" as external stocks of ideas (1997: 531). Adopting this logic, we measured external search breadth as the number of different types of external parties an individual interacted with. Respondents were provided with a list of 11 different types of partners that could constitute their external network: (1) business partners, (2) competitors, (3) consultants, (4) customers and users, (5) government relations, (6) private research institutes, (7) professional and trade institutions, (8) standard setting organizations, (9) suppliers, (10) universities, or (11) other partners, and were asked which ones they interacted with. The external search breadth variable ranges from 0 to the maximum of 11 different types of collaborators.

Attention to information sources. We recognized that different types of information sources may vary in the search time they take. Thus, we created two attention measures—one measuring allocation of attention to external people and one measuring allocation of attention to external written information. Given the need to acknowledge the finite amount of time available for search, both measures asked respondents to distribute 100 points to show how they allocated their time between external and internal information sources. By doing so, we forced survey respondents to recognize the fixed nature of their time and how allocation to one type of search source reduced the attention available for another search source.

Attention to external people. To capture the extent to which an individual allocated time with people inside versus outside the firm, we asked respondents to "Please distribute 100 points to indicate the relative amount of time, during your typical workday, that you interact with individuals from each category listed below": (1) within your organization (e.g., individuals in your office, organizational members, etc.), (2) outside your organization (e.g., customers, suppliers, alliance partners, governmental contacts, university contacts, investors, etc.). We divided the points each individual devoted to interacting with people outside their organization by 100. This variable ranges from 0 (only attending to internal people) to 1 (only attending to external people). As an alternative measure, we captured the absolute amount of time our sample devoted to people outside IBM. We multiplied the relative measure of attention to external people with the minimal time informants estimated for search: 30 percent of the number of hours worked per week. This provides a lower bound of the hours spent on external people.

Attention to external written information. We asked a similar question with respect to external written information sources. We measured the relative time individuals spent searching internal versus external written information sources with a survey item that asked: "Please distribute 100 points to indicate the relative amount of time, during your typical workday, that you spend in each category listed below." The two options were: (1) searching internal written information sources (e.g., websites, manuals, firm information), and (2) searching external written information sources (e.g., written information about customers, markets, partners, competitors, etc.). To develop the variable, we divided the number of points individuals devoted to external written information outside the organization by 100. This variable thus ranges from 0 (only attending to internal information) to 1 (only attending to external written information). To construct an alternative absolute measure of attention to external written information, we multiplied this measure by the minimal time informants estimated for search: 30 percent of hours worked per week.

Control variables

We control for a range of alternative explanations that may affect the number, quality, and novelty of patents produced by each individual.

Type of search role. We include a dummy variable taking the value 1 if an individual is a Distinguished Engineer as they are appointed for their length of employment within IBM. We also include a separate dummy with the value 1 if an individual is both a Distinguished Engineer and an Academy member—meaning that the baseline is only those elected to the Academy of Technology.

Hours worked per week. Individuals who work more hours may be capable of more search time by virtue of spending more time at work. To control for this, we include a measure of the average number of hours worked every week as indicated by survey data.

Tenure within the firm. We control for the effect that tenure may have on individual's experience in developing information sources by measuring the number of years an individual worked for IBM. Several scholars have noted how individuals' pace in producing both publications and patents slows down later in their careers (Allen and Katz, 1986; Gruber *et al.,* 2013). We thus include a main effect and the squared effect to capture the possibility of diminishing returns to tenure within the firm.

Academic publications. Because scientific publications can affect attention to external search breadth (Katz, Tushman, and Allen, 1995), we control for scientific engagement by calculating the number of scientific publications produced in the last three years prior to the survey.

PhD degree. PhDs may be more likely to search outside the firm and have broad external networks. We thus control for whether the scientists and engineers have a PhD using a dummy variable (e.g., Gruber *et al.,* 2013). We collected these data from individuals' LinkedIn Profile, IBM's employee website, and through Google searches.

Gender. We coded a dummy variable taking the value 1 if the individual is male. We assessed this by looking through LinkedIn web pages, and used a name probability tool that gives a probability that a person is male or female based on their name. When uncertain, we corroborated this by looking at the pictures of LinkedIn profiles and individual web pages.

LinkedIn profile. The presence on professional platforms such as LinkedIn allows people to expand their professional network, potentially allowing them to grow their external search breadth. LinkedIn is by far the largest such network with close to 300 million users. We thus created a dummy variable equal to 1 if the person had a registered LinkedIn profile.

Estimation model

Our dependent variables are skewed with some individuals accounting for a disproportionally large share of patents. We normalized the patent counts by the number of inventors to account for individuals who collaborate with a large number of patent inventors. We use a quasi-maximum likelihood (QML) Poisson regression to predict the patent outcomes, which has been shown to be applicable even though the dependent variable is not a count variable. Since the Poisson model is in the linear exponential family, the coefficient estimates remain consistent as long as the mean of the dependent variable is correctly specified. QML Poisson standard errors are consistent even if the underlying data-generating process is not Poisson (Gourieroux, Monfort, and Trognon, 1984). The dependent variable is weighted by the number of inventors on a patent, but the QML model can be used when the dependent variable takes non-integer values. QML Poisson is suitable because it imposes little structure on the underlying data distribution and is a more conservative estimate of the coefficients due to the larger standard errors compared to negative binomial regressions.

In our models, we controlled for patents granted prior to the survey by using lagged cumulative dependent variables, which control for the innate ability of people to produce more patents. It is plausible that individuals who have been active in the past in producing patents will continue to do so in the future, and thus the lagged variable accounts for unobserved heterogeneity (Heckman and Borjas, 1980; Stuart, 2000). Regressions with lagged dependent variables produce consistent estimates if error terms are uncorrelated over time. Autocorrelation can affect other coefficient estimates downwards (Leiponen and Helfat, 2010). However, it is generally preferred to include lagged dependent variables as omitting them can introduce bias. Standard errors can also be potentially lower in models with lagged dependent variables, resulting in overstating the significance tests. In supplementary analyses, we excluded the lagged dependent variables, and the results are substantially the same as those reported in the paper. Standard errors were also substantially the same, suggesting that too small standard errors are not causing the significant results. As the marginal effects are slightly lower for what we report, we think our results show a lower bound of the effects (Leiponen and Helfat, 2010).

RESULTS

The descriptive statistics and correlations among the variables are presented in Table 1. The

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Table 1. Descriptive statistics

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Dependent variables																							
1. Patents (post-survey)	0.57	1.56	0	16.74																			
2. Patents (pre-survey)	2.1	4.35	0	34.9	0.78																		
3. Novel patents (post-survey)	0.24	0.8	0	10.26	0.94	0.71																	
4. Novel patents (pre-survey)	1.06	2.49	0	17.98	0.8	0.96	0.76																
5. Quality-adjusted patents (post-survey)	0.03	0.14	0	1.42	0.67	0.63	0.65	0.68															
6. Quality-adjusted patents (pre-survey)	0.69	2.17	0	31.35	0.57	0.75	0.54	0.77	0.74														
Independent variables																							
7. External search breadth	5.84	2.29	0	11	0.11	0.03	0.13	0.07	0.1	0.07													
8. Attention to external people	0.37	0.22	0	0.95	−0.05	−0.08	−0.03	−0.03	−0.03	−0.04	0.28												
9. Attention to external people absolute	6.31	4.11	0	24	−0.03	−0.06	−0.01	−0.01	0.01	0.01	0.3	0.95											
10. Attention to external written information	0.45	0.24	0	1	0.05	0.08	0.03	0.09	0.07	0.12	0.22	0.29	0.28										
11. Attention to external written information absolute	7.69	4.39	0	22.95	0.08	0.11	0.05	0.12	0.15	0.2	0.27	0.3	0.38	0.93									
Control variables																							
12. Hours worked per week	57.13	10.01	12	100	0.06	0.07	0.06	0.07	0.16	0.15	0.18	0.09	0.35	0.02	0.35								
13. Academic papers	2.97	8.31	0	100	0.34	0.3	0.23	0.3	0.44	0.4	0.11	0.04	0.06	0.1	0.14	0.09							
14. Tenure	23.21	8.76	1	46	0.03	0.03	0.04	0.05	0.05	0.05	−0.05	−0.09	−0.11	−0.14	−0.15	−0.11	−0.05						
15. Academy member only	0.25		0	1	0.04	0.04	0.01	0.05	0.13	0.09	0.05	−0.06	−0.03	0.05	0.05	−0.01	0.19	−0.1					
16. Distinguished Engineer only	0.44		0	1	0.02	−0.02	0.05	−0.01	−0.03	−0.04	0.04	0.1	0.07	0.00	0.00	0.00	−0.06	−0.1	−0.51				
17. Academy member and Distinguished Engineer	0.31		0	1	−0.05	−0.02	−0.07	−0.04	−0.09	−0.04	−0.08	−0.05	−0.05	−0.05	−0.04	0.02	−0.11	0.2	−0.39	−0.59			
18. PhD degree	0.33		0	1	0.07	0.11	0.04	0.09	0.00	0.08	0.07	−0.01	−0.01	0.1	0.1	0.00	0.21	−0.19	0.18	−0.12	−0.05		
19. Gender is male	0.83		0	1	−0.02	−0.04	−0.03	−0.05	−0.13	−0.09	0.08	0.04	0.06	0.06	0.1	0.09	−0.09	−0.1	−0.13	0.16	−0.05	−0.03	
20. LinkedIn profile	0.85		0	1	0.09	0.11	0.08	0.11	0.04	0.06	0.07	0.04	0.02	0.09	0.08	−0.02	0.06	0.07	−0.13	0.24	−0.13	0.03	−0.1

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correlations between the independent and control variables are relatively modest, suggesting that multicollinearity is not a problem. However, the dependent variable is highly correlated with the lagged dependent variables. Table 2 presents the results for the QML Poisson regressions predicting the dependent variable (quantity of patents) measured *after* the survey was distributed, controlling for the lagged cumulative number of patents *before* the survey.

Model 1 is the baseline model that only includes the control variables. Model 2 includes the main effect of external search breadth and establishes a positive linear relationship between external search breadth and innovation outcomes. Model 3 adds the squared term to test whether there are diminishing returns to external search breadth. Model 4 adds the main effects of attention to external people and external written information. Model 5 includes an interaction between attention to external people and external written information. Models 6 and 7 replicate the prior two models by using an absolute measure of attention rather than a relative measure of attention. Model 8 adds squared effects for attention to external people and external written information. Model 9 adds interaction variables between external search breadth and attention to external people and attention to external written information. In addition to the variables of Model 9, Model 10 includes the interaction between external search breadth and the squared effects of attention to external people and external written information. In what follows, we explain the logic driving these models.

External search breadth

Our first exercise was to assess the main effect of external search breadth at the individual level and its effect on innovation outcomes. Models 2–7 show a positive and significant main effect of external search breadth on innovation outcomes at the 1 percent level. Model 3 tested possible nonlinearities and found that the squared effect was insignificant. Thus, we can conclude that external search breadth has a significant and linear positive relationship with the number of patents produced.

Attention allocation

We analyzed the allocation of attention in two different ways to reflect potential differences in the effort exerted when searching either written or human sources of information. Model 4 included the main effect of attention to external people as well as external information. The coefficient for attention to external people was negative and significant at the 5 percent level. Similarly, the coefficient for attention to external written information was negative and significant at the 1 percent level. This finding suggests that attending to external written information and external people actually lowered innovation outcomes for the average person in our sample. We also assessed whether combining attention to external people and external written information created additional advantages in Models 5 and 7. We tested the interaction effect between the two, and the effect was insignificant.

In addition, we wanted to account for the possibility of nonlinearities in attention between internal and external information sources. We thus included squared effects of allocation of attention to external people and external written information. The coefficient for attention to external people squared was insignificant in Model 8, while the coefficient for attention to external written information squared was negative and significant at the 1 percent level. This indicates that increased levels of attention to external people as well as external information decreased innovative outcomes. In contrast to what prior research on the variance hypothesis would predict, the average person in our sample who allocated more attention to external rather than internal information sources of both types (people and written sources) was *less* likely to produce patents.

Interaction effects between external search breadth and attention allocation

Our reasoning has thus far assessed the effects of external search breadth and attention to external information sources independently and overlooked how these conditions may jointly shape innovation outcomes. As external search breadth increases, people may need to allocate more attention to information sources outside the firm in order to reapply and recombine what is learned. Model 9 therefore included interaction effects between external search breadth and attention to external people as well as written information. We also assessed potential nonlinearities by adding the squared effects in Model 10. Our first conclusion is that allocating attention to external people moderates the effect of external search breadth on patents produced, while allocating attention to external information does

Table 2. Predicting number of post-survey patents controlling for past performance

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Cumulative lagged DV	0.148 **	0.151 **	0.151 **	0.155 **	0.155 **	0.154 **	0.154 **	0.154 **	0.162 **	0.165 **
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)
Hours worked per week	−0.102+	−0.178 **	−0.178 **	−0.071	−0.075	0.042	0.055	−0.012	−0.165 **	−0.136+
	(0.062)	(0.053)	(0.052)	(0.067)	(0.055)	(0.071)	(0.054)	(0.087)	(0.056)	(0.079)
Academic papers	0.101 **	0.095 *	0.096 *	0.127 **	0.126 **	0.134 **	0.137 **	0.143 **	0.151 **	0.164 **
	(0.020)	(0.045)	(0.047)	(0.008)	(0.006)	(0.007)	(0.013)	(0.012)	(0.053)	(0.034)
Tenure within IBM	0.054	0.039	0.040	0.038+	0.039 *	0.039+	0.038	0.032	0.031 *	0.023+
	(0.034)	(0.034)	(0.034)	(0.022)	(0.020)	(0.023)	(0.024)	(0.022)	(0.012)	(0.013)
Tenure within IBM squared	−0.002 *	−0.001+	−0.001+	−0.002 **	−0.002 **	−0.002 *	−0.002 *	−0.001 *	−0.001 **	−0.001 *
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Distinguished Engineer only[a]	0.084	−0.016	−0.016	0.124	0.124	0.127	0.126	0.106	−0.022	−0.133+
	(0.171)	(0.146)	(0.145)	(0.193)	(0.195)	(0.190)	(0.192)	(0.164)	(0.116)	(0.071)
Academy member and Distinguished Engineer[a]	−0.407+	−0.295	−0.297	−0.377	−0.377	−0.380	−0.381+	−0.315	−0.129	−0.084
	(0.216)	(0.187)	(0.194)	(0.245)	(0.246)	(0.237)	(0.231)	(0.225)	(0.199)	(0.187)
PhD degree	−0.371+	−0.277	−0.279	−0.360+	−0.363+	−0.343+	−0.328+	−0.254	−0.216	−0.034
	(0.197)	(0.171)	(0.176)	(0.209)	(0.197)	(0.208)	(0.186)	(0.197)	(0.163)	(0.162)
LinkedIn profile	0.364 **	0.415 *	0.413 *	0.380 **	0.382 **	0.339 **	0.311 **	0.310 **	0.502 **	0.538 **
	(0.126)	(0.173)	(0.170)	(0.090)	(0.095)	(0.085)	(0.110)	(0.094)	(0.187)	(0.138)
Gender is male	0.278	0.188	0.188	0.326	0.326	0.305	0.297	0.301	0.336 **	0.310 **
	(0.253)	(0.223)	(0.223)	(0.227)	(0.225)	(0.227)	(0.218)	(0.208)	(0.114)	(0.072)
External search breadth		0.300 **	0.299 **						0.576 **	0.764 **
		(0.035)	(0.038)						(0.071)	(0.066)
External search breadth squared			0.004							
			(0.035)							
Attention to external people				−0.170 *	−0.172 *			−0.256 *	−0.616 **	−0.377 **
				(0.071)	(0.075)			(0.102)	(0.096)	(0.099)
Attention to external people absolute						−0.191 **	−0.184 *			
						(0.071)	(0.078)			
Attention to external written information				−0.192 **	−0.185 **			−0.162 **	−0.225 **	−0.169 *
				(0.033)	(0.054)			(0.039)	(0.034)	(0.067)
Attention to external written information absolute						−0.188 **	−0.183 **			
						(0.039)	(0.032)			
Attention to external people × attention to external written information					0.022					
					(0.085)					

Table 2. Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Attention to external people absolute × attention to external written information absolute							−0.037			
							(0.065)			
Attention to external people squared								0.140		0.191 *
								(0.087)		(0.081)
Attention to external written information squared								−0.199 **		−0.336 **
								(0.042)		(0.055)
External search breadth × attention to external people									0.426 **	0.422 **
									(0.067)	(0.063)
External search breadth × attention to external written information									0.030	0.020
									(0.033)	(0.039)
External search breadth × attention to external people squared										−0.361 **
										(0.050)
External search breadth × attention to external written information squared										0.027
										(0.039)
Constant	−1.891 **	−1.867 **	−1.872 **	−1.865 **	−1.883 **	−1.824 **	−1.780 **	−1.747 **	−2.501 **	−2.418 **
	(0.267)	(0.263)	(0.252)	(0.198)	(0.218)	(0.202)	(0.233)	(0.303)	(0.274)	(0.444)
Log likelihood	−257.222	−249.484	−249.482	−251.313	−251.280	−251.131	−250.959	−247.259	−226.609	−213.685
Number of observations	330	330	330	330	330	330	300	330	330	330

[a] Compared against Academy of Technology member only.
Two-tailed tests. Standardized coefficients with Huber-White sandwich robust standard errors clustered by nation in parentheses. The dependent variables in all models are the number of patents weighted by team size. The robustness checks reported in the supporting information show the results for alternative DVs. DV = direct variable.
$+p < 0.1$; $*p < 0.05$; $**p < 0.01$

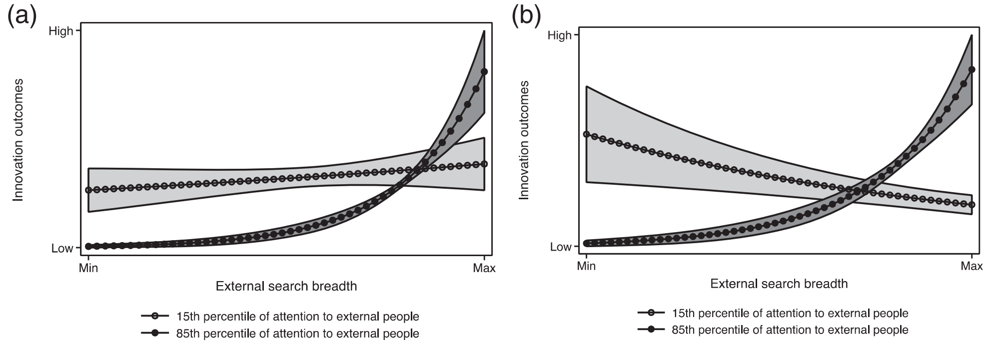

Figure 1. (a, b) Predictive marginal effects of external search breadth with 95 percent confidence intervals at two different levels of attending to external people (15th and 85th percentiles). These results are based on the estimates from Model 6 and 7, respectively

not. People who spent more time outside the firm were only innovative if they also cultivated external search breadth. Put differently, people gained more from external search breadth when they allocated more time to people outside the firm.

Interpreting the results is not trivial in nonlinear models, and we thus plot the marginal effects at two different levels of attention to external people. Figure 1(a, b) plots the marginal effects at the 15th and 85th percentiles of attention to external people using the results from Model 9 (using only the main effect of the attention variables) and Model 10 (including the squared of the attention variables), respectively.

Three noteworthy findings emerge from these figures. First, individuals who pay little attention to external people (15th percentile) are unaffected by increasing their external search breadth as a horizontal line fits within the 95 percent confidence intervals. Second, these individuals are consistently innovative, and often more innovative than those who allocate more attention to external people. Third, individuals with high attention to external people (85th percentile) gain the most from their external search breadth. It is when attention and breadth are coupled that people are the most innovative. As one member of the Academy who spent a lot of time on external search breadth explained: "We talked to everyone we could think of that mattered in the [technology] community to try and find out what their views of it were. How they saw it playing out, rather than just sitting inside IBM and speculating [where] IBM people talk to other IBM people and they get a consensus as to what they all think." This Academy member had deliberately broadened his search breadth and was allocating more time to it—relying on his Academy colleagues to keep him up to date with events going on inside the firm.

One way to interpret these results is to apply Gouldner's (1957) conception of locals and cosmopolitans. Locals, with low external search breadth, still produced innovative outcomes if they allocated their attention to colleagues inside the firm. Indeed, many locals in our sample were very innovative regardless of their external search breadth. Cosmopolitans, with great external search breadth, only produced greater innovative outcomes when they allocated more attention to external people. Taken together, these findings suggest that there are two distinct but equifinal individual approaches to a successful innovative search: a local approach emphasizing attention to people inside the firm and a cosmopolitan approach that cultivates and attends to a broad network of external people.

As a *post hoc* analysis, we wanted to document the extent of lower-performing search behavior. A scatter plot of external search breadth and attention to external people weighted by the number of observations is illustrated in Figure 2. Echoing the descriptive statistics, we see a weak (0.28) albeit positive relationship between the variables. We drew lines for the 25th and 75th percentiles for the two variables to divide the sample into low (25th percentile) versus high search breadth (75th percentile) and low (25th percentile) versus high (75th percentile) attention to external people. As expected, most respondents were in the middle, and the numbers in the respective corners in Figure 2 illustrate how many individuals fall into the corners exhibiting either higher- or lower-performing search behavior.

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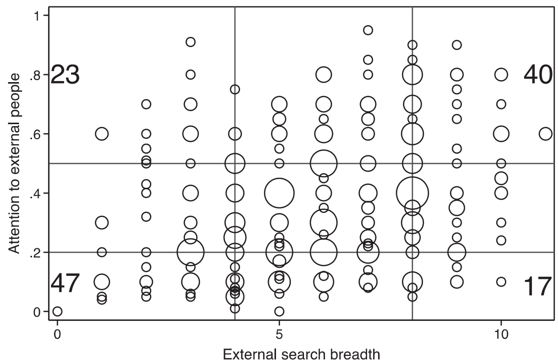

Figure 2. Scatter plot of external search breadth and attention to external people weighted by the number of observations. A larger circle means that we have more people who have this combination of external search breadth and attention to external people. The solid lines are drawn at the 25th and 75th percentiles to analyze people in the four corners of low versus high attention of external search breadth, and low versus high attention to external people. The numbers in these corners illustrate the number of observations we found in each corner to illustrate the extent of those with behavior leading to lower innovation outcomes. There is a weak positive correlation (0.28) as illustrated in the descriptive statistics, but we observe many different combinations

According to our results, the southwest and northeast corners are where people are more innovative, whereas the northwest and southeast corners are characterized by lower-performing innovative behavior. Of the people with high external search breadth (75th percentile and above), about 30 percent (17/(17 + 40)) demonstrated low attention to external people and were "social butterflies." These people cultivated broad networks, but did not increase their attention to these external people—spreading finite attention across a broader variety of industry relationships. Conversely, at low external search breadth (up to the 25th percentile), we found that 33 percent (23/(23 + 47)) allocated their attention to external people without cultivating search breadth—maintaining monogamous relations to only one type of external partner. These people spent a great deal of time outside the organization but did not adequately cultivate breadth among different types of ties. Thus, we can conclude that (1) about a third of the sample exhibited lower-performing search behavior, and (2) that the extent of this behavior is similar for both low and high external search breadth.

Our explanation for this result builds upon field data collected from interviews and workshops. Respondents with high external search breadth that failed to adequately attend to external partners built, as a result, a broad network of thin ties and were unable to harness the benefits from these relationships. Respondents who spent a great deal of time outside the firm but did not cultivate external search breadth failed to garner the requisite variety needed for innovative outcomes. For instance, one person with high attention to external people mentioned how he only talked to people from universities. That said, we explored other possible explanations for these different patterns of search behavior by investigating differences in the control variables between higher- and lower-performing groups. Table S3 in Appendix S1 compares descriptive means between the two groups. We included an additional question probing respondents about their motivations for engaging with external partners to test whether motivation affected whether they were high or low performing. There are no significant differences between these means for high- and low-performing groups. Thus, we can rule out other possible explanations, such as gender, education, and motivation for search, lending more credence to the explanations we propose.

Robustness checks

First, we conducted several robustness checks to strengthen the inferences reported in Table S2 in Appendix S1. An important consideration is that not all patents are equal. Using two established measures, we reestimated our models with two additional dependent variables: novel patents and quality-adjusted patents. Models 8 and 9 have novel patents as the dependent variable, and Models 10 and 11 have quality-adjusted patents as the dependent variable. There are some small differences across the regressions, but the key findings reported prevail: external search breadth remains positive and significant, and the interaction effect between external search breadth and attention to external people is positive. In sum, our results are consistent across all three dependent variables.

Second, we assessed whether working in teams of inventors or alone could affect the results. Models 12 and 13 ignore patents with a single inventor, whereas Models 14 and 15 only look at single inventor patents for each individual. These models show some small differences, but the main result persists: external search breadth remains positive and significant, and attention to external people moderates this relationship.

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Third, we did a median split of individuals' allocation of attention to external people to assess the effect of external search breadth at different levels of attention. The marginal effects illustrated in Figure 1(a, b) show that external search breadth is beneficial only when coupled with more attention to people outside the organization, but has no effect at lower levels of attention to people outside the organization. The positive effect between external search breadth on innovation outcomes that we found in the regressions is driven by people who spend a large amount of time with external people. We assessed whether this is reproducible in a sample split and not an artifact of the many covariates included in the regression. Model 16 shows the results of external search breadth at below or equal to the median of attention to people outside the organization. Model 17 shows the same with the sample above the median.[2] As expected, the coefficient for external people is not significant in the sample below the median and is positive above the median. People who allocated more attention to people outside the organization stood to gain from external search breadth, whereas people who focused on local colleagues were unaffected. This underscores the robustness of the positive interaction effect between external search breadth and attention to external people.

Fourth, we found an unexpected negative effect of the number of hours worked per week on innovation outcomes. To assesses what drives these results, we split this continuous variable into three chunks (fewer than 40 hours, between 40 and 70 hours, and more than 70 hours). The results in Models 18 and 19 show that the negative result is driven by those who work more than 70 hours a week, and that our basic results remain robust.

Fifth, we clustered standard errors based on the location of individuals as people in the same countries could have similar innovation strategies. We replicated Models 6 and 7 using location dummies rather than clustered standard errors at the country level in Models 20 and 21. The results are very similar to those using clustered standard errors by location.

Sixth, we followed the approach suggested by Imbens (2003) to perform a sensitivity analysis to show the degree to which omitted variable bias could be responsible for the statistically significant relationship between external search breadth and innovation outcomes. This analysis shows how strongly correlated an omitted variable must be to be simultaneously correlated with a treatment or independent variable and the dependent variable in order to make the effect of the treatment variable disappear (see Wang, 2014, for an application). Building on Harada's (2012) extension of Imbens, we visually analyzed whether an omitted variable is likely to exist and the conditions it would need to fulfill, through three steps, using his generalized sensitivity analysis. We found that it is unlikely that an omitted variable would cause the effect of external search breadth to disappear.

All of our robustness checks show that our main findings are robust to alternative dependent variables including the novelty and quality of patents produced. The interaction effect between external search breadth and attention to external people is also visible in a sample split below and above the median of attention to external people. Our results are also robust to alternative ways to measure the control variables, specifying the model using country-specific dummies, and is unlikely to suffer from omitted variable bias.

DISCUSSION

The discovery of novel ideas does not occur at the firm level but is the cumulative result of innovative search conducted by individuals (Laursen and Salter, 2006; Li *et al.,* 2013; Rosenkopf and Almeida, 2003). Individuals in key scientific and technical boundary spanning and search roles can exact significant influence (Fleming and Waguespack, 2007; O'Mahony and Ferraro, 2007), affecting the alliances firms develop (Rosenkopf, Metiu, and George, 2001) and the influence firms exercise (Dokko and Rosenkopf, 2010). The implication is that understanding how boundary spanners straddle the firm and its external environment is a key question for strategy. However, much of the research on innovation search has focused on how firms overcome problems of local search (Li *et al.,* 2013). Little is known as to how individual search behaviors affect innovation outcomes (see Nerkar and Paruchuri, 2005, for an exception). If firms in dynamic environments are unlikely to benefit from centralized search processes (Cohen and

[2] The number of observations in Models 8a and 8b are not exactly the same as we have several observations at exactly the median. The results are insensitive to different ways of splitting the sample around the median.

Levinthal, 1990), then it is critical that we develop a rich understanding of how search strategies at the individual level affect innovation outcomes.

The variance hypothesis has received a great deal of support in prior research at firm, team, and individual levels. On the whole, our research confirms the variance hypothesis—on average, individuals with greater external search breadth were more innovative than those who collaborated with a more narrow range of external people, and this effect did not dissipate. However, little research has accounted for the opportunity cost associated with innovation search. While scholars have theorized that external search breadth may have its constraints at the firm level (Laursen and Salter, 2006; Leiponen and Helfat, 2010), research designs rarely appreciate how boundary spanners' allocation of attention, a finite resource, affects the benefits that can be extracted from external search.

When we took into account the finite time people have available and how they allocated their attention, our results became more nuanced by showing that the benefits of external search breadth are moderated by individual's allocation of attention to external information sources. In doing so, we discovered two equifinal search approaches that led to innovative outcomes: (1) high external search breadth coupled with high attention to external information sources (cosmopolitans), or (2) low external search breadth coupled with high attention to internal information sources (locals). As Figure 1(a) demonstrates, both the cosmopolitan and local approaches to search can achieve innovative results. Gouldner (1957) used the terms cosmopolitans and locals to differentiate between technical experts and company men. Our sample were all technical experts within the same firm, avoiding the unobserved heterogenity associated with studies of multiple firms. Yet, we still uncover variation in search strategies and effectiveness. Our research demonstrates that no "one strategy fits all" when it comes to predicting a successful innovative search even among a common pool of elite technical experts who act as boundary spanners.

The limits of external search breadth

While our research confirms that variance in external search breadth is important to fostering innovation, it also identifies a critical boundary condition under which it can detract from innovation outcomes. The effects of external search breadth on innovation outcomes are conditioned on how well individuals attend to people as sources of information. The same does not hold with respect to written information sources. This is an important insight. External search breadth can enable individuals to tap divergent mind-sets and ideas (Allen, 1977; Ancona and Caldwell, 1992; Tushman, 1977) when they devote adequate attention to the personal relationships under-riding those information sources. Our results show that people as external information sources take more time than external written sources of information—possibly in order to learn how external ideas developed in one context can be reapplied elsewhere (Hansen, 1999; Murray and O'Mahony, 2007).

Although there are many ways to measure strong and weak ties (Marsden and Campbell, 1984), if one determination of strength is the degree to which one spends time on those ties, then, in our research, external search breadth is more effective when coupled with strong rather than weak ties. As one full-fledged cosmopolitan Academy member explained: "I have tended to reduce the effort on internal networking in my current role … [maintaining a broad external network] takes significant time and requires you to do this with genuine interest, otherwise this is a waste. You have to remain motivated to maintain contact even when there has been no apparent value for many years." This engineer was deliberate in how he allocated his time, and pulling back on internal networking allowed him to both deepen and broaden his external ties.

The unexpected innovative power of locals

What would surprise Gouldner (1957) is that locals (who lacked external search breadth and allocated most of their attention to people inside the firm) were highly innovative. Locals, in his mind, demonstrated low commitment to external reference groups, which would limit the "requisite variety" needed to produce new innovations. But, we found that locals produced more patents when they allocated more absolute as well as more relative attention to people inside the firm. Even though our sample was tasked with innovative search, internal colleagues played a key role for many in our sample. Few individuals spent the majority of their time on external people, and this benefited rather than detracted from innovative outcomes. Thus, those who are not skilled at cultivating external search breadth can still be innovative by

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focusing their attention on colleagues inside the firm. Internal search can be a stable source of innovation (e.g., Grant, 1996) in a firm the size of IBM. As one Academy member explained, internal search at IBM could be complicated:

> *The view from inside IBM of what IBM is and how it behaves is nothing like what you see from the outside. For instance, the image I always had of IBM was that it was very slow. Actually, it is too fast. Inside IBM there is constant churn, just like Silicon Valley, of new ideas and changing alliances. The outcome is that the decisions that are visible on the outside seem to take forever. But from the inside it is the insane churn of new ideas, and new alliances, you can't even keep track of it, it's just insane.*

Locals' attention to internal affairs may thus be a critical need for large firms competing in dynamic innovation environments. In this manner, locals may gain greater trust and access to internal information than peers pursuing a "thin" external search. Introducing new ideas into an organization's products, processes, and systems requires "mutual ownership" (Fleming *et al.,* 2007: 462), and attention to internal colleagues can engender trust in a person's ability to bring people together in service of collective, creative outcomes (Ibarra, Kilduff, and Tsai, 2005; Long Lingo and O'Mahony, 2010; Obstfeld, 2005). Locals can innovate by focusing on internal search and developing the relationships needed to bring innovations to fruition rather than cultivating external search breadth.

If these results seem intuitive, consider that this was not the case for all in our sample. As Burt argued: "network brokerage is a craft more than a commodity so benefits typically vary widely between people" (2010: 195). The social butterflies in our sample conducted a thin external approach to search without devoting adequate attention to those ties. In this case, individuals incurred the costs of cultivating external search breadth without capitalizing on the benefits. The "monogamous external" searchers allocated attention outside the organization without developing search breadth and were less innovative. These individuals spent a great deal of time with the same types of external partners—as a result of familiarity, history, shared experiences, or enduring social relationships that were not refreshed over time.

Our findings suggest that even talented senior experts with search autonomy may have difficulty determining how to allocate their attention to achieve innovative results. Many individuals juggle how to allocate their attention not just between work and home (Evans, Barley, and Kunda, 2004; Perlow, 1998) but between competing responsibilities at work. For example, academics have to allocate their attention between conducting research and presenting it to a broader audience with implications for scholarly innovation and productivity. In our research, neither the social butterfly approach nor the monogamous external approach to search was likely to lead to higher innovative outcomes. Dedicated search roles were offered as a reward to elite technical experts with a proven record of innovation (e.g., Gambardella *et al.,* 2013). Yet, even within this sample, people have different strengths, weaknesses, preferences, and capabilities, and while some chart distinct search paths that leverage their distinct skill sets, others have more trouble. What is counterintuitive is that the most effective search approaches operated at extremes—where individuals allocate attention either inside or outside the firm rather than trying to seek a balance between the two as Allen (1977) predicted.

Individual search behavior

As a response to fluid, fast-paced, and mobile work environments, firms often place individuals in key search roles to enhance access to external sources of information (Martin and Eisenhardt, 2010; Rosenkopf and Almeida, 2003). In technical and scientific industries, individuals in dedicated search roles are often at the forefront of managing these relationships, and their ability to do so has real consequences for the firm (Dokko and Rosenkopf, 2010; Fleming and Waguespack, 2007; Rosenkopf *et al.,* 2001). Individuals in our study considered themselves to be both scouts and representatives for IBM: "I am going to this [conference] because I am one of IBM's representatives so I need to keep my pulse on what is happening." Technical and scientific experts working in this capacity are often rewarded with autonomy over their own work (Bailyn, 1991; Gambardella *et al.,* 2013; Katz *et al.,* 1995), but we know little about how these individuals navigate innovation search once receiving this autonomy. Yet, this is critical to understanding how knowledge from external sources is absorbed and applied by the firm (Cohen and Levinthal, 1990). Individuals' external search breadth has consequences for subsequent rates of innovation for both individuals and the firm. One implication is that individuals' self-awareness of their own search strengths and weaknesses may be critical to crafting an effective innovation search strategy. Rather than point to one formula, our research suggests that at least two distinct search approaches can be effective in producing innovative outcomes.

Limitations and directions for future research

Our findings have several limitations that open new avenues for future research. The current literature largely favors the external sourcing of innovations (e.g., Dahlander and Gann, 2010), but in a firm as large as IBM, internal resources can also be critical to generating novel ideas. Thus, one boundary condition to the generality of our results may be firm size. Maintaining currency inside the firm can present its own challenge in a firm as large as IBM. Given IBM's size, the amount of variance inside the firm may be substantially more than what is available within smaller firms. An alternative but sympathetic explanation is that, given IBM's size and competitive position, the translation of innovative ideas into patents requires more internal coordination. Thus, we expect our findings to hold for large global firms competing in dynamic environments.

The cross-sectional design of our study raises several concerns about endogeneity. One concern stems from the fact that we don't know whether the search patterns observed are a function of personality traits, preferences, experiences, or some combination. We account for survey respondents' inherent ability to patent using lagged cumulative dependent variables. Our regressions include several variables such as tenure inside the firm, education, and social networking to account for differences in skills. Despite these precautions, whether the results we find are deliberate or unintentional behaviors cannot be fully determined from our data. Future research could examine how the different search patterns we discovered parse among these possibilities (e.g., Gruber *et al.,* 2013). We are thus careful in interpreting our results as causal, but rather as noteworthy correlations with important implications.

Our sample is a select group of elite scientists and engineers. The benefit of studying this group is that they were all tasked with innovation search and given the autonomy to do so within the same firm. It was impossible to study individuals not hired for these roles to parse out selection effects. But the selection of this group is similar to all studies of employees, as no organization that we know would hire or promote people at random. While our sample is a select group, it is useful for studying the limits of the variance hypothesis. Our findings have relevance for many firms of similar size that incorporate innovation boundary spanning, search, or scouting roles. Field work could provide more detail on the practices (Barley and Kunda, 2001) that individuals used to manage external search breadth.

We investigated one type of innovation output three ways (by using the volume, novelty, and quality of patents produced), and while this output was valued by IBM, other types of innovation outcomes exist and would be important to consider in situations where patents are an ineffective means of appropriability. We were able to rule out some alternative explanations that might drive different patterns of search behavior. However, it is possible that the scientists and engineers who were low performing with respect to patenting outcomes provided other benefits to the firm. One question that remains is how the innovation outcomes we measured affect firm performance in the near and long term. Future research would do well to uncover how the patents awarded to the engineers and scientists we studied extend or renew a firm's portfolio. Doing so would illuminate how individuals dedicated to search affect changes in firms' performance overall. If recent research on open innovation (Chesbrough, Vanhaverbeke, and West, 2006; Dahlander and Gann, 2010) is any indication, individuals in technical leadership positions are likely to play increasingly important roles in firms' innovation strategies and deserve our attention.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1 Definitions of variables and robustness checks.