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Effects of Geographic Search on Product Innovation in Industrial Cluster Firms in China

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ABSTRACT The literature suggests that cluster firms may undertake both local and nonlocal geographic searches for knowledge that contributes to their product innovation, and that cluster firms must balance their local and nonlocal searches for product innovation. Yet, previous research has seen local and nonlocal searches as one-dimensional, rather than two-dimensional, activities involving search breadth and depth. In this study, we show that local search and nonlocal search are balanced by jointly considering the breadth and depth of geographic search, and that the optimal balance depends on industry dynamism. Using a sample from two industry clusters in China, we find positive relationships between relative local search depth, relative nonlocal search breadth, and the product innovation of cluster firms. Relative local search depth and relative nonlocal search breadth contribute more to product innovation in stable industries than in dynamic industries.

KEYWORDS China, cluster firms, geographic search, product innovation

地理搜寻对中国集群企业产品创新的影响

摘要

相关文献表明，集群企业可以采取本地搜寻和非本地搜寻来获取产品创新所需的知识，同时，企业必须平衡这两种地理搜寻方式以利用各自的优势。但是，已有的研究将本地搜寻和非本地搜寻视作单一维度的活动，而非包括了搜寻宽度和搜寻深度的两维搜寻活动。本研究认为，通过同时考虑地理搜寻的宽度和深度，集群企业可以实现本地搜寻与非本地搜寻的平衡，而且，优化的平衡依赖于产业的动态性水平。利用来自中国两个产业集群的数据，本研究实证发现，相对本地搜寻深度和相对非本地搜寻宽度有助于促进集群企业的产品创新绩效，它们对稳定性集群企业的作用要大于动态性集群企业。

关键词：中国，集群企业，地理搜寻，产品创新

INTRODUCTION

Product innovation is strategically critical to the performance and survival of cluster firms (Porter, 1990, 1998; Saxenian, 1994). *Cluster firms* are firms within an industrial cluster – a geographically proximate group of interconnected companies and associated institutions in a particular industrial field, linked by commonalities and complementarities (Porter, 1998, 2000). Firms augment their organizational knowledge through searches for knowledge that can foster product innovation (Grant, 1996; Levinthal & March, 1981). Geographically proximate cluster firms with interconnected business fields (Porter, 1990, 1998) can augment their knowledge bases by integrating internal knowledge (Nonaka, Reinmoeller, & Senoo, 1998) and, importantly, by accumulating knowledge from beyond their organizational boundaries (Rosenkopf & Nerkar, 2001; Von Hippel, 1994). With the introduction of the open innovation model (Chesbrough, 2003), this latter process, known as *external knowledge search*, is vital for cluster firms' product innovation (Phene, Fladmoe-Lindquist, & Marsh, 2006; Zhang & Li, 2010).

Recent research concerning cluster firms' external knowledge searches has focused on the geographic dimension (Ahuja & Katila, 2004; Sidhu, Commandeur, & Volberda, 2007). Two types of geographic search have been differentiated: *local search* delineates knowledge search within the geographic boundaries of industrial clusters, and *nonlocal search* goes beyond those boundaries. While both local (Baptista & Swann, 1998; Porter, 1990, 1998; Saxenian, 1994) and nonlocal searches (Camagni, 1991; Ratti, Bramanti, & Gordon, 1997) can contribute to cluster firm innovation, both convey costs and effects that are negatively related to innovation (Beaudry & Breschi, 2003; Giuliani & Bell, 2005; Owen-Smith & Powell, 2004; Shaver & Flyer, 2000). The issue is therefore how cluster firms might balance their local and nonlocal searches to obtain the best external knowledge (Bathelt, Malmberg, & Maskell, 2004). Thus, furthering the debate regarding local and nonlocal balance will enrich our understanding of innovation in cluster firms (Gertler & Levitte, 2005; McKelvey, Alm, & Riccaboni, 2003; Oinas & Malecki, 2002).

Drawing on extant critical literature (Katila & Ahuja, 2002; Laursen & Salter, 2006) and organizational learning theory (Levinthal & March, 1993; March, 1991), we propose that, to gain the best insights into the balance between local and nonlocal searches, they should be differentiated according to two *distinctive* dimensions: *search depth* and breadth. Thus, we categorize geographic search as local search breadth, local search depth, nonlocal search breadth, and nonlocal search depth. In developing our hypotheses, we suggest that all four types of geographic search behaviours may influence product innovation. To further explore the role of the local–nonlocal search balance in product innovation, following Uotila, Maula, Keil, and Zahra (2009), we examine the influence of two geographic search orientations – relative local search depth and relative nonlocal search breadth – on

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product innovation for cluster firms. In our study, *relative local search depth* refers to the relative importance of local search depth activities vs. nonlocal search depth activities; *relative nonlocal search breadth* refers to the relative importance of nonlocal search breadth activities vs. local search breadth activities. We also explore the moderating effect of industry dynamism on the relationship between geographic search orientation and product innovation.

THEORETICAL BACKGROUND AND HYPOTHESES

Local and Nonlocal Search

External knowledge search has a geographic dimension. *Geographic search* refers to knowledge search within and beyond firms' geographic location (Ahuja & Katila, 2004; Sidhu et al., 2007). Cluster firms often pursue both searches simultaneously since both affect product innovation in specific ways. Cluster firms must balance their local and nonlocal searches (Scott, 1998), as shown by recent empirical studies reporting that neither local nor nonlocal searches *alone* decisively contribute to innovation. On one hand, local search has uncertain effects on product innovation: it may be positively related (Baptista & Swann, 1998; Porter, 1990, 1998; Saxenian, 1994) or negatively related (Beaudry & Breschi, 2003; Suarez-Villa & Walrod, 1997). The relevance of spatial proximity for knowledge exchange may actually be exaggerated (Boschma, 2005; Gertler, 2003) because the ability to benefit from neighbouring knowledge depends largely on context (Beaudry & Breschi, 2003; Shaver & Flyer, 2000). On the other hand, nonlocal search also has complex effects on product innovation. Cluster firms may be able to link systematically with nonlocal knowledge sources (Camagni, 1991; Ratti et al., 1997), but to acquire nonlocal knowledge that may facilitate product innovation (Asheim & Isaksen, 2002; Bathelt et al., 2004), there may be limited ability to access and utilize large amounts of geographically distant knowledge (Phene et al., 2006) because nonlocal knowledge may be difficult to adapt and incorporate (Owen-Smith & Powell, 2004).

The complexities of local and nonlocal searches make it important for cluster firms to balance both forms to foster product innovation (Bathelt et al., 2004). However, researchers have not yet shown specifically how to achieve such a balance and have not established the relative importance of local vs. nonlocal searches (Gertler & Levitte, 2005; McKelvey et al., 2003; Oinas & Malecki, 2002). One possible reason for the gap in current research is that extant studies predominantly assumed that local and nonlocal sources – such as customers, suppliers, and universities – provide homogeneous knowledge (Camagni, 1991; Ratti et al., 1997). Assumptions about the homogeneity of local and nonlocal knowledge have an important, and we believe undesirable, implication, because they overlook the search for heterogeneous knowledge – search breadth – as a *distinctive* search behaviour. On the contrary, knowledge from different local and nonlocal sources is often heterogeneous (Audretsch & Feldman, 2004; Gilbert, McDougall, &

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Audretsch, 2008). Innovation search varies according to two distinctive dimensions – breadth and depth – and both play different roles in innovation (Katila & Ahuja, 2002; Laursen & Salter, 2006). However, we are unclear about the different roles for breadth and depth in both local and nonlocal searches. Based on these observations, we next engage with the literature on organizational learning theory and innovation search to propose four geographic search behaviours pursued by cluster firms.

Search Depth and Breadth

The organizational learning literature has delineated *exploitation activities* as refinement, choice, production, efficiency, selection, implementation, and execution; and *exploration activities* as search, variation, risk-taking, experimentation, play, flexibility, discovery, and innovation (March, 1991). Innovation management research has applied this exploitation–exploration framework (Benner & Tushman, 2002, 2003; He & Wong, 2004) to show that exploration and exploitation draw on different resources and generate significantly different performance outcomes (Levinthal & March, 1993). Therefore, a balance between exploitative and exploratory activities is considered optimal for firm performance (Benner & Tushman, 2002; Levinthal & March, 1993).

Based on organizational learning theory (Levinthal & March, 1993; March, 1991), innovation search efforts vary according to two distinct dimensions (Grimpe & Sofka, 2009; Katila, 2002; Katila & Ahuja, 2002; Laursen & Salter, 2006): *search breadth*, which describes how widely firms explore new knowledge; and *search depth*, which describes how deeply firms reuse, or exploit, existing knowledge. Empirically, both search breadth and depth can significantly affect innovation (Katila, 2002; Katila & Ahuja, 2002; Laursen & Salter, 2006).

Type of geographic search. Differentiating the depth dimension from the breadth dimension of geographic search, a cluster firm's geographic search may include four categories: local search breadth, local search depth, nonlocal search breadth, and nonlocal search depth. These four geographic search behaviours may impact product innovation in different ways and degrees.

Local search breadth refers to the number of local external knowledge sources or search channels that cluster firms may use for innovative activities (Katila & Ahuja, 2002; Laursen & Salter, 2006). One firm may search widely for knowledge from local sources; another may have few local potential search channels. Thus, the two firms have different local search breadth. Cluster firms that have broad local search possibilities can enjoy enhanced innovation potential (Asheim & Isaksen, 2002; Keeble, 2000; Porter, 2000) because they can obtain various valuable knowledge elements from different local knowledge sources, such as local competitors, suppliers, and research institutes (Katila, 2002; Katila & Ahuja, 2002). Similarly, the

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shared knowledge basis enables them to transfer sticky and tacit knowledge from local actors and continuously combine and recombine similar and different knowledge to produce new knowledge and innovation (Bathelt et al., 2004). Importantly, through broad local knowledge search, cluster firms can meaningfully and usefully understand local knowledge (Bathelt et al., 2004) without particular investments (Grabher, 2002). Therefore, we propose:

Hypothesis 1: Cluster firms' local search breadth will positively relate to their product innovation.

Local search depth refers to how deeply cluster firms draw on local external knowledge sources (Katila & Ahuja, 2002; Laursen & Salter, 2006). Even if two different cluster firms have the same types of local knowledge sources, they can vary in the depth of their local searches. Cluster firms draw deeply from local sources for building and sustaining virtuous exchanges and collaborations with local actors (Laursen & Salter, 2006). They can use their ties with local partners to access local knowledge, identify valuable knowledge elements within that knowledge, and combine them in many different and significant ways. Therefore, deep local searches can facilitate innovation (Porter, 2000). Thus, we propose:

Hypothesis 2: Cluster firms' local search depth will positively relate to their product innovation.

Nonlocal search breadth refers to the number of nonlocal external knowledge sources that cluster firms rely on to facilitate product innovation, that is, nonlocal sources that can provide new knowledge (Owen-Smith & Powell, 2004; Simmie, 2003). Some may search nonlocal sources widely; others may search only a few. Relatively speaking, knowledge from outside clusters is new and important (Bathelt et al., 2004; Owen-Smith & Powell, 2004), so broad searches from nonlocal sources can provide more potential combinations of various novel nonlocal knowledge elements (Katila, 2002; Katila & Ahuja, 2002). Therefore, we propose:

Hypothesis 3: Cluster firms' nonlocal search breadth will positively relate to their product innovation.

Nonlocal search depth refers to how deeply cluster firms draw on different nonlocal external knowledge sources. The depth of nonlocal searches may differ for various cluster firms. For example, even if two cluster firms have the same types of nonlocal knowledge sources, one may draw heavily from several nonlocal sources and another may draw heavily from only one. Deep nonlocal search enhances product innovation because cluster firms can gain a deeper understanding of the nature and value of nonlocal knowledge and then improve the efficiency and reliability of their product innovation (Katila & Ahuja, 2002). Therefore, we propose:

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Hypothesis 4: Cluster firms' nonlocal search depth will positively relate to their product innovation.

Relative nonlocal search breadth. Firms have limited resources (Oakey, 1995; Penrose, 1959) and limited cognitive capabilities (Conner & Prahalad, 1996; Simon, 1957). Thus, to maximize the effect of their limited resources and cognitive capabilities on product innovation, cluster firms must know the individual impact of the four types of geographic search on product innovation and, more importantly, know their relative importance. Although all four types of geographic search can individually contribute to product innovation, their individual contributions may vary. In other words, cluster firms should allocate resources to geographic search behaviours that offer the best relative contributions to product innovation. We expect that local search depth will more positively influence innovation than nonlocal search depth, and nonlocal search breadth will have a greater effect than local search breadth. Next we explore the role of relative local search depth and relative nonlocal search breadth on cluster firms' product innovation (Uotila et al., 2009).

Relative nonlocal search breadth refers to the relative importance of nonlocal search breadth vs. local search breadth. It describes situations in which cluster firms rely on more nonlocal knowledge sources than on local knowledge sources. Modern product innovation requires firms to master highly specific knowledge about different users, technologies, and markets (Laursen & Salter, 2006). Broadly searching for new knowledge outside industrial clusters can thus facilitate product innovation by adding various new knowledge elements to the existing knowledge set (Katila & Ahuja, 2002). For example, nonlocal customers may provide new knowledge that is unavailable from local customers, such as information about the characteristics and trends of customer demands in nonlocal markets. Similarly, nonlocal suppliers may provide new knowledge about advanced materials and manufacturing processes that are somewhat different from those local suppliers can provide. Relatively speaking, cluster firms can obtain more new knowledge from nonlocal searches than from local searches given the same search breadth because they may be more familiar with local knowledge than nonlocal knowledge (Bathelt et al., 2004; Gertler, 2003). Therefore, cluster firms that undertake broader nonlocal searches should have access to more varied new knowledge elements for combination (Katila, 2002; Katila & Ahuja, 2002; Nelson & Winter, 1982). New combinations, in turn, provide choices for creating new products (von Hippel, 1988; Laursen & Salter, 2006). Utilization of new, technologically distant knowledge allows firms to avoid familiarity traps and provides a basis for innovation (Ahuja & Lampert, 2001). Broader spatial searches have been shown empirically to positively affect innovativeness (Sidhu et al., 2007), and broader nonlocal search has been shown to be valuable for achieving breakthrough innovations (Phene et al., 2006). Similarly, cluster firms develop radically new products by using formal, scientific knowledge jointly with actors outside their regions (Asheim & Isaksen, 2002). Thus we propose:

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Hypothesis 5: Cluster firms' relative nonlocal search breadth will positively relate to their product innovation.

Relative local search depth refers to the relative importance of a cluster firm drawing more deeply from local knowledge sources than nonlocal knowledge sources. Increased relative local search depth can contribute positively to product innovation in at least two ways. First, relative local search depth can reduce product innovation costs by making knowledge search more predictable and reliable (Eisenhardt & Tabrizi, 1995). Repeated searches for similar knowledge can facilitate the development of organizational routines (Katila & Ahuja, 2002; Levinthal & March, 1981), enhance the efficiency of innovation searches, and reduce search costs. Geographic proximity may lower costs associated with face-to-face communication and the transfer of local knowledge (Tallman, Jenkins, Henry, & Pinch, 2004), and therefore allow firms to detect new directions and endeavours that other firms are taking, allowing them to align their initiatives with industry trends appropriately (Brown & Duguid, 2000). Similarly, location in an industrial centre allows traded and nontraded inputs to be provided at a lower cost (Baptista & Swann, 1998). For example, geographical, social, and cognitive proximity between cluster firms and their local partners allows cluster firms to find local actors more easily, which yields lower costs for exchanging daily knowledge and innovative cooperation (Audretsch & Feldman, 1996; Lagendijk & Oinas, 2005). Thus, although deep search for nonlocal knowledge may also boost product innovation, deep search for local knowledge can contribute relatively more to product innovation because of lower search costs.

Second, deep searches for local knowledge make it easier for cluster firms to develop partner-specific absorptive capacities, which in turn enable them to assess and assimilate received knowledge (Maskell, 2001), to identify innovation opportunities worth pursuing (Abrahamson & Rosenkopf, 1993), and to recognize high-growth markets for exploitation. In addition, enhanced partner-specific absorptive capacities enable cluster firms to develop joint problem-solving mechanisms with local partners (McEvily & Marcus, 2005). Being located in a cluster may better facilitate the transfer of tacit knowledge, which is more difficult to transfer and deploy across borders (Bresman, Birkinshaw, & Nobel, 1999), and is best conveyed through face-to-face interaction (Maskell, 2001). Tacit knowledge is widely acknowledged to be an important component of innovation (Dosi, 1988). Thus, cluster firms that search deeply in a cluster may be better able to receive timely and tacit knowledge regarding the market and technology from local partners, and hence have stronger product innovation (Gilbert et al., 2008). Cluster firms that overemphasize local search depth may face knowledge overload, but that would normally not be a major problem because knowledge is constantly being evaluated and tested in the industrial cluster context (Bathelt et al., 2004). In summary, cluster firms can more easily transfer and absorb local

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(tacit) knowledge with lower costs through deep local searches rather than through deep nonlocal searches. Thus we propose:

Hypothesis 6: Cluster firms' relative local search depth will positively relate to their product innovation.

Moderating Effect of Industry Dynamism

Relative local search depth can play a greater role in stable industries than in dynamic industries because repeated deep local searches enable firms to obtain, with relatively lower cost, a deep understanding of the nature and value of local knowledge, which is often similar to the knowledge they already have and which can be used for efficient and reliable incremental product innovation (Ahuja & Katila, 2004; Katila & Ahuja, 2002). In stable industries, where customer preferences, technologies, and competitive dynamics change little and the potential for steady improvement is considerable, incremental product innovation is desirable. That is, in stable settings, local knowledge acquired today will still be somewhat useful tomorrow (March, 1991; Weick, 1991). By contrast, in dynamic industries, where customer preferences, technologies, and competitive dynamics undergo dramatic changes, environmental upheaval is often so great that knowledge becomes rapidly obsolete (March, 1991; Miller & Shamsie, 2001) requiring new knowledge to create new products and to respond quickly to industry changes. Relative local search depth behaviour allows cluster firms to acquire local knowledge that is already similar to their knowledge base, so it cannot help in creating new products. Therefore, we propose:

Hypothesis 7a: Relative local search depth will have a greater impact on cluster firms' product innovation in a stable industry than in a dynamic one.

Relative nonlocal search breadth will play a greater role in product innovation in dynamic industries than in stable industries. Cluster firms that search broadly from nonlocal sources acquire knowledge elements that are new to their knowledge base (Katila & Ahuja, 2002), providing potential for new combinations or new products (von Hippel, 1988), which is especially important if cluster firms are to survive and grow in dynamic industries where customer preferences, technologies, and competitive dynamics change rapidly and where firms face risks that their core technologies will become rapidly obsolete (Sorensen & Stuart, 2000). Thus relative nonlocal search breadth behaviour is critical for facilitating product innovation in dynamic industries. By contrast, in stable industries, customer preferences, technologies, and competitive dynamics change little. Thus, cluster firms might prefer to gradually and steadily improve their products rather than develope radically new products. Similar or related knowledge can enhance the efficiency and

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reliability of that strategy (Katila & Ahuja, 2002). New knowledge from various nonlocal sources may fail to improve existing products because of the low predictability and reliability of broad nonlocal searches, although it can help cluster firms create more and new highly innovative products (Katila & Ahuja, 2002). Therefore, we propose:

Hypothesis 7b: Relative nonlocal search breadth will have a greater impact on cluster firms' product innovation in a dynamic industry than in a stable one.

METHOD

Sample and Data Collection

To test our hypotheses, we conducted a questionnaire survey in Zhejiang Province, one of China's most developed economic regions. In 2007, Zhejiang had more than 460 industry clusters with 2.52 trillion RMB industrial output value, and 6.7 million employees. Zhejiang's industry clusters involve most industry sectors including machinery manufacturing, textile, garment, pharmaceutical, and information technology.

We randomly selected 700 firms in the Shaoxing textile industry cluster and Taizhou pharmaceutical industry cluster as samples. In 2007, the Shaoxing textile industry cluster, located in Shaoxing City, was the largest and most advanced textile industry base in China with 74.7 billion RMB industrial output value. In 2009, the Taizhou pharmaceutical industry cluster, located in Taizhou City, was one of largest pharmaceutical industry bases in China with 36.2 billion RMB industrial output value. Both clusters are spontaneous industry clusters rather than constructed industry clusters, which range from technopoles and industrial parks to incubators and export processing zones. They are typical of the spontaneous clusters found elsewhere in the world, such as the ceramics cluster in Santa Catarina, Brazil, the surgical instruments cluster in Sialkot, Pakistan, the furniture cluster in Jutland, Denmark, and the spectacle frame cluster in Belluno, Italy.

We drew samples from the textile and pharmaceutical industries because they have widely contrasting degrees of dynamism (Henderson, Miller, & Hambrick, 2006); that is, they have varying degrees of innovation, technological change, supply instability, competitive rivalry, and market growth (Aldrich, 1979; Dess & Beard, 1984). The *China Statistical Yearbook* reports that from 1985–2009, China's pharmaceutical industry increased its workforce by an average of 4.7 percent annually, outperforming the textile industry's annual employee growth rate of 0.3 percent. Also, the pharmaceutical industry increased its average annual growth rate of gross industrial output value by 19.1 percent, while the textile industry grew by 13.3 percent. From 2001–2009, China's pharmaceutical industry showed an average annual growth rate of 13.3 percent in the number of patents granted,

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compared with the textile industry's 3.8 percent. These statistics strongly indicate that the pharmaceutical industry is much more dynamic, with rapid technological change, great innovation, volatile growth, and unstable demand. In contrast, the textile industry is much more stable, with slower and more consistent growth and little technological or competitive change. Therefore, the pharmaceutical industry represents a dynamic industry and the textile industry represents a stable industry.

Two researchers competent in both Chinese and English and with substantial research experience in the subject area in China prepared the original questionnaire in English and then translated it into Chinese. To avoid cultural bias and ensure validity, the Chinese version was back-translated into English. We pretested a preliminary version on six executives to ensure that informants would find the measurement items acceptable and identifiable, and then we incorporated their feedback into a revised version of the questionnaire. To enhance the effective response rate, we used several methods outlined by Westphal (1998). First, the survey packet contained a cover letter that described the main goal and potential value of the study. Second, the participants were informed that if they returned the completed questionnaires, they would receive a summary report of the study.

We administered the questionnaires on site. A major concern in survey research is that a single respondent may answer all questions consistently, causing common method bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). To reduce that potential, we designed the questionnaire to include two separate parts. Part one contained questions regarding the firm's innovation search behaviours, strategic orientations, and environments. Part two asked about innovation performance, financial performance, and organizational demography (Zhang & Li, 2010). For each cluster firm, we asked one manager to complete part one and one financial officer to complete part two. Because managers know best about innovation and operation behaviours, and financial officers know more about financial and innovative outcomes, such a design can improve response accuracy and alleviate respondents' burdens (Zhang & Li, 2010).

We obtained valid data from 229 firms, representing an effective participation rate of 32.7 percent. Of the responding firms, 53.3 percent were in the textile industry and 46.7 percent were in the pharmaceutical industry. To assess the non-response bias, we compared early respondents with late respondents and found no significant differences in firm size, age, and sector. We also compared responding firms with non-responding firms and found no significant differences in firm size, age, and sector. The firms reported that top executives completed 51.5 percent of the questionnaire; marketing, R&D, and product managers filled out 48.5 percent of the questionnaire for part one, and financial officers filled out the questionnaire for part two. This increased our confidence in the quality of data because the respondents were experienced and knowledgeable about the issues being studied (Kumar, Stern, & Anderson, 1993).

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Measures

Product innovation. We used product innovation as the dependent variable, measured as the share of turnover achieved with new products, following previous literature (see, e.g., Grimpe & Sofka, 2009; Laursen & Salter, 2006).

Local search breadth and nonlocal search breadth. Based on our fieldwork, following previous studies (see, e.g., Grimpe & Sofka, 2009; Laursen & Salter, 2006), we chose ten sources of external knowledge (suppliers, customers, competitors, enterprises in other sectors, R&D institutes, university, conferences, trade fairs or exhibitions, service intermediaries, others) that may be used for firm innovation. We used each knowledge source as a separate search channel. Thus, we measured the search breadth as the number of different knowledge sources that a firm draws on in its innovative activities. We coded each of the ten different knowledge sources as a binary variable: 0 indicating no use and 1 indicating use of the knowledge source for innovation. The value of search breadth was the sum of the codes for all ten knowledge sources. We followed the cluster literature (Almeida & Kogut, 1997; Weterings & Boschma, 2009) in defining local and nonlocal knowledge sources. *Local space* refers to Shaoxing City and Taizhou City, respectively, and *nonlocal space* refers to space outside Shaoxing City and Taizhou City, respectively. We measured local search breadth and nonlocal search breadth respectively.

Local search depth and nonlocal search depth. Following Laursen and Salter (2006), we defined search depth as the extent to which a cluster firm draws intensively from external knowledge sources. Respondents rated the extent to which their firm draws intensively from each of the ten knowledge sources. If a cluster firm used a given knowledge source to a high degree, we coded the knowledge source as 1. If a firm did not use a given knowledge source or used it to a low or medium degree, we coded it as 0. The value of search depth was the sum of the codes for all ten knowledge sources. We measured local search depth and nonlocal search depth respectively.

Relative nonlocal search breadth. Relative nonlocal search breadth refers to the relative importance of nonlocal search breadth vs. local search breadth. The value of relative nonlocal search breadth was the difference between the value of nonlocal search breadth and that of local search breadth.

Relative local search depth. Relative local search depth refers to the relative importance of a cluster firm's local search depth vs. its nonlocal search depth. Thus, in our study, the value of relative local search depth was the difference between the value of local search depth and that of nonlocal search depth.

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Control variables. Our analysis included control variables: firm age, firm size, firm R&D intensity, return of assets (ROA), internationalization orientation, and sector. We controlled for firm age as the number of years from the founding year to 2009 and controlled for firm size as a natural log of the total number of full-time employees in 2009 (Li & Atuahene-Gima, 2002; Zhang & Li, 2010). We controlled for firm R&D intensity as a firm's R&D expenditures divided by firm sales (Katila & Ahuja, 2002; Laursen & Salter, 2006). We also controlled for firm performance, because financial performance can affect innovation (Katila & Ahuja, 2002). We used ROA as a firm performance measure (Hitt, Hoskisson, Johnson, & Moesel, 1996; Katila & Ahuja, 2002). Internationalization can also influence innovation performance (Cheng & Bolon, 1993; Kafouros, Buckley, Sharp, & Wang, 2008), so we measured internationalization orientation (Cronbach's $\alpha = 0.92$) with a four-item scale as the intensity of international activities (entering new foreign markets, expanding international business operations, supporting international business operations, and financing international business activities) that a cluster firm has undertaken over the past three years. Finally, to control for industrial influences on firm innovation, we created one dummy contrasting the textile industry (1) with the pharmaceutical industry (0).

Analyses

We employed ordinary least squares (OLS) regressions to analyze the effect of geographic search on product innovation. Model 1, with only control variables, is a benchmark for testing the effects of four geographic searches (local search breadth, local search depth, nonlocal search breadth, and nonlocal search depth), relative local search depth, and relative nonlocal search breadth on product innovation. In Models 2, 3, 4, and 5, we added local search breadth, local search depth, nonlocal search breadth, and nonlocal search depth respectively to Model 1 to examine their individual impacts. In Model 6, we added the four geographic search variables to control variables to further confirm their impact. In Model 7, we added both relative local search depth and relative nonlocal search breadth to the control variables to examine their impact. We estimated separate models for the textile and pharmaceutical industries rather than pooling them and using interactions to test cross-industry differences (Henderson et al., 2006). In Model 10, we tested the effects of relative local search depth and relative nonlocal search breadth with the sample of firms in the textile industry. We tested the effects of relative local search depth and relative nonlocal search breadth with the sample of firms in the pharmaceutical industry in Model 13. We compared the different influence of relative local search depth and relative nonlocal search breadth between textile firms and pharmaceutical firms. Additionally, the value of Variance Inflation Factor (VIF) was below 3, indicating that multicollinearity is not a serious problem in our study.

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RESULTS

Table 1 reports the means and standard deviations of the dependent, independent, and control variables and their correlations. Table 2 reports the results of various regression models explaining the product innovation of cluster firms.

Hypothesis 1 predicts that local search breadth is positively related to the product innovation of cluster firms. In Model 2, the coefficient of local search breadth is positive and significant ($\beta = 0.33$, $p < 0.001$). The coefficient of the variable of local search breadth remains positive and significant at a marginal level ($\beta = 0.13$, $p < 0.10$) in Model 6. Thus, Hypothesis 1 is supported. Hypothesis 2 predicts that local search depth is positively related to the product innovation of cluster firms. The coefficient of local search depth is positive and significant in Model 3 ($\beta = 0.16$, $p < 0.05$) and remains positive and significant at a marginal level in Model 6 ($\beta = 0.15$, $p < 0.10$). Thus, Hypothesis 2 is supported. Hypothesis 3 predicts that nonlocal search breadth can contribute to the product innovation of cluster firms. The coefficient of nonlocal search breadth is positive and significant in both Model 4 ($\beta = 0.43$, $p < 0.01$) and Model 6 ($\beta = 0.35$, $p < 0.001$). Thus, Hypothesis 3 is supported. Hypothesis 4 predicts that nonlocal search depth is positively related to the product innovation of cluster firms. In Model 5, the coefficient of nonlocal search depth is positive but not significant ($\beta = 0.05$, n.s.). It turns negative and significant at a marginal level ($\beta = -0.14$, $p < 0.10$) in Model 6 where other dimensions of search are included. This suggests that nonlocal search depth may incur costs to knowledge acquisition and negatively influence the innovation of cluster firms. Thus, Hypothesis 4 is not supported.

Hypothesis 5 predicts that relative nonlocal search breadth is positively related to the product innovation of cluster firms. In Model 7, the coefficient of relative nonlocal search breadth is positive and significant ($\beta = 0.23$, $p < 0.01$). Thus, Hypothesis 5 is supported. Hypothesis 6 predicts that relative local search depth plays a positive role in the product innovation of cluster firms. The coefficient for relative local search depth is reported as positive and significant in Model 7 ($\beta = 0.17$, $p < 0.05$). Our results show significant positive coefficients for the independent effect of relative local search depth, lending support to Hypothesis 6.

Hypothesis 7a predicts that relative local search depth will have a greater impact on the product innovation of cluster firms in a stable industry than in a dynamic one. As indicated in Model 10, which includes textile industry firms, the regression coefficient for relative local search depth is positive and statistically significant ($\beta = 0.20$, $p < 0.05$). In Model 13, which includes pharmaceutical industry firms, the regression coefficient for relative local search depth is positive but not statistically significant ($\beta = 0.10$, n.s.). Those results indicate that relative local search depth plays a positive role in product innovation in the stable textile industry, and has no significant role in product innovation in the dynamic pharmaceutical industry. That is, relative local search depth plays a greater role in the stable

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Table 1. Descriptive statistics and correlation matrix

	Mean	*S.D.*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1. Product innovation	0.34	0.21												
2. Firm age	11.96	6.96	0.16*											
3. Firm size	5.43	1.30	0.10	0.38***										
4. Firm R&D intensity	0.06	0.07	0.14*	0.03	0.15*									
5. ROA	0.18	0.16	0.08	0.11	0.15*	0.11†								
6. International orientation	3.30	1.08	0.24***	0.12†	0.32***	0.10	0.16*							
7. Sector	0.53	0.50	−0.01	−0.27***	−0.17*	−0.15*	−0.14*	−0.26***						
8. Local search breadth	8.85	2.12	0.38***	0.06	−0.03	0.08	0.18**	0.30***	0.02					
9. Local search depth	2.41	2.49	0.24***	0.02	0.17**	0.08	0.11	0.43***	−0.07	0.36***				
10. Nonlocal search breadth	7.27	3.47	0.42***	0.20**	0.26***	0.05	0.10	0.59***	−0.18*	0.59***	0.36***			
11. Nonlocal search depth	1.41	2.33	0.10	−0.04	0.14*	−0.06	0.01	0.39***	−0.08	0.21**	0.64***	0.40***		
12. Relative nonlocal search breadth	−1.58	2.80	0.23***	0.20**	0.34***	0.01	−0.01	0.50***	−0.21**	0.03	0.17*	0.79***	0.34***	
13. Relative local search depth	1.00	2.05	0.17**	0.06	0.06	0.17**	0.12†	0.08	0.01	0.20**	0.49***	−0.02	−0.36***	−0.18**

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

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Table 2. Results of OLS regression

Variables	*All firms*							*Firms in textile industry*			*Firms in pharmaceutical industry*		
	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*	*Model 13*
Control variables													
Firm age	0.18*	0.14*	0.18*	0.13*	0.18*	0.11†	0.15*	0.17†	0.15	0.17†	0.16†	0.09	0.15
Firm size	−0.05	0.01	−0.06	−0.06	−0.05	−0.03	−0.09	−0.20†	−0.18†	−0.24*	0.08	0.10	0.06
Firm R&D intensity	0.13†	0.11†	0.12†	0.13*	0.13*	0.10†	0.12†	−0.02	−0.01	−0.01	0.26*	0.22*	0.23*
ROA	0.04	−0.01	0.03	0.04	0.04	0.01	0.05	0.04	−0.03	0.01	−0.01	−0.05	0.01
International orientation	0.24**	0.13†	0.17*	−0.00	0.22**	−0.02	0.13	0.42***	0.08	0.28*	−0.00	−0.11	−0.03
Sector	0.12†	0.09	0.11†	0.13†	0.12†	0.10	0.13†						
Local search breadth		0.33***				0.13†			0.06			0.32*	
Local search depth			0.16*			0.15†			0.22†			0.06	
Nonlocal search breadth				0.43**		0.35***			0.44**			0.09	
Nonlocal search depth					0.05	−0.14†			−0.15			−0.09	
Relative local search depth							0.17*			0.20*			0.10
Relative nonlocal search breadth							0.23**			0.27*			0.07
F value	4.07**	7.41***	4.30***	8.60***	3.54**	7.10***	4.71***	5.40***	5.85***	5.27***	2.75*	3.58**	2.13*
R^2 squared	0.10	0.19	0.12	0.22	0.10	0.25	0.15	0.19	0.32	0.25	0.12	0.25	0.13
Adjusted R^2	0.08	0.17	0.09	0.19	0.07	0.21	0.12	0.16	0.27	0.20	0.08	0.18	0.07

Notes: Standardized coefficients are reported in the table. † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed test).

industry than it plays in the dynamic industry. Thus, Hypothesis 7a is supported. Hypothesis 7b predicts a greater impact of relative nonlocal search breadth on the product innovation in a dynamic industry than in a stable one. The regression coefficient for relative nonlocal search breadth is positive and statistically significant ($\beta = 0.27$, $p < 0.05$) in Model 10 and is positive but not statistically significant ($\beta = 0.07$, n.s.) in Model 13. These results indicate that relative nonlocal search breadth plays a positive role in product innovation in the stable textile industry, but has no significant role in the dynamic pharmaceutical industry. Thus, Hypothesis 7b is not supported.

DISCUSSION

Theoretical Implications

In this study of cluster firms and the effects on their product innovation, we find that local search breadth, local search depth, and nonlocal search breadth play positive roles. However, we find that nonlocal search depth plays no positive role, perhaps because cluster firms have limited capability to access and deeply utilize large amounts of geographically distant knowledge (Phene et al., 2006). Excessive reuse of the same nonlocal knowledge may limit the potential for new recombination innovations (Katila & Ahuja, 2002).

Moreover, and importantly, we find that both relative local search depth and relative nonlocal search breadth play significant roles in cluster firms' product innovation. Cluster firms may balance local and nonlocal searches by simultaneously emphasizing relative local search depth and relative nonlocal search breadth. For local searches, they need to emphasize search depth; for nonlocal searches, they need to emphasize search breadth. Specifically, to improve product innovation, cluster firms need to search in the local area more deeply than they search in the nonlocal area. They must also search more widely in the nonlocal area than they search in the local area.

Interestingly, we further find that relative local search depth and relative nonlocal search breadth matter only in the stable textile industry, but not in the dynamic pharmaceutical industry. On one hand, we find that textile firms benefit significantly from both local search depth and nonlocal search breadth, but not from local search breadth or nonlocal search depth. Thus, the two dimensions of relative geographic search can facilitate innovation. Textile firms do not, however, significantly improve their innovation performance by conducting R&D internally. On the other hand, we find that pharmaceutical firms benefit greatly from local search breadth, but not from local search depth, nonlocal search depth, and nonlocal search breadth. We also find that internal R&D efforts play an important role in product innovation in the pharmaceutical industry. Thus, firms in the stable textile industry depend on both local search depth and nonlocal search breadth for

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product innovation, while firms in the dynamic pharmaceutical industry depend on local search breadth and internal R&D investment.

Our study advances understanding of the role of geographic search in the product innovation of cluster firms. Studies' findings are inconsistent about the role of local searches: some find that local search positively impacts innovation (Baptista & Swann, 1998; Porter, 1990, 1998; Saxenian, 1994) while others report no significant influence (Beaudry & Breschi, 2003; Suarez-Villa & Walrod, 1997). Our study finds that local search breadth, local search depth, and relative local search depth can contribute to product innovation, which advances our understanding of the role of local search. The impact of nonlocal search on cluster firms' innovation is still unclear. For example, some studies indicate that nonlocal search has positive effects (e.g., Asheim & Isaksen, 2002; Giuliani & Bell, 2005) while others suggest a limited impact (Phene et al., 2006). Recently, intercommunity relationships (density, geographic distance, and domain overlap) were found to have an inverted U-shaped relationship with the community's growth in China's high-tech industrial clusters (Zhang, Li, & Schoonhoven, 2009). This suggests that nonlocal search plays a complicated role that would benefit from further exploration. Through differentiating the depth dimension from the breadth dimension of nonlocal search, our study empirically finds that nonlocal search breadth, but not nonlocal search depth, helps cluster firms improve their innovation performance. Moreover, our study finds that relative nonlocal search breadth can contribute to the product innovation of cluster firms. This advances the research on the role of nonlocal search.

Moreover, our study contributes to the cluster literature's ongoing discussion of the balance between local and nonlocal search. Although many researchers have highlighted the importance of the local–nonlocal search balance, most prior studies have seen local or nonlocal search as one-dimensional rather than two-dimensional. By distinguishing the depth of search from the breadth of search, we can better test the different roles of the depth and breadth of local or nonlocal search, and then explore the local–nonlocal search balance when jointly considering the two dimensions. Our findings of a positive relationship between relative local search depth, relative nonlocal search breadth, and the product innovation of cluster firms supports the argument that a local–nonlocal balance is required (e.g., Bathelt et al., 2004; Scott, 1998), and also explicitly shows specific approaches for cluster firms to achieve search balance. Our study suggests that the differentiation between search breadth and depth in both local and nonlocal knowledge search constitutes a useful framework that may further show how cluster firms balance local and nonlocal knowledge searches. Furthermore, our findings also contribute to understanding the moderating effect of industry dynamism on the relationships between cluster firms' geographic searches and product innovation. Our results show that relative local search depth and relative nonlocal search breadth matter only in a stable industry, but not in a dynamic industry.

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Practical Implications

Our contributions also have managerial implications. Prior studies have suggested that cluster firms must balance local and nonlocal searches, but have not provided specific suggestions or strategies for firms to achieve balance. Our findings not only indicate the individual roles of four types of geographic searches in the product innovation of cluster firms but also indicate that cluster firms may benefit by increasing their emphasis on relative local search depth and relative nonlocal search breadth by exploring the relative importance of different geographic searches. Additionally, our findings suggest that, under low dynamism, cluster firms should search deeply in the local cluster area and widely beyond the local cluster area.

Limitations and Future Research Implications

Our study has several limitations that future research should address. First, we used data from firms in two of China's industry clusters to examine our hypotheses. As a result, the results may have questionable generalizability, suggesting further research in other settings. For example, the Chinese context for local search may encompass knowledge search from firms in other or distant industries. In Western contexts, that would be considered nonlocal search, because Chinese and Western clusters have different attributes. Nonlocal search in the Chinese context may also differ from nonlocal search in the Western context. Therefore, future studies should explore the role of unique attributes of Chinese clusters in the formation and evolution of Chinese firms' search behaviours, and should test whether Western theories of innovation search and industrial cluster can be applied to the Chinese context (Barney & Zhang, 2009).

Second, we analyze only the effects of industry dynamism on the relationship between geographic search and product innovation. Future research should examine the influences of other moderating variables such as absorptive capability and strategic factors. Third, we examine the linear relationships between geographic search and product innovation. Some studies have suggested a nonlinear relationship between innovation search and product innovation (Katila & Ahuja, 2002; Laursen & Salter, 2006). Studies based on China's high-tech clusters also indicate that intercommunity relationships have an inverted U-shaped relationship with the focal community's growth (Zhang et al., 2009). Therefore, future research should explore the nonlinear relationships between cluster firms' geographic searches and product innovation.

Fourth, we examine the relative importance of local search depth and nonlocal search depth, and the relative importance of nonlocal search breadth and local search breadth in the product innovation of cluster firms. Future studies should explore the impact of competitors' search behaviour in the formation and evolution of geographic searches, because a firm's search behaviour depends on the

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actions of competitors (Katila & Chen, 2008). Interestingly, recent research finds that foreign presence in an industry positively affects the product innovation of local firms in the same industry (Li, Chen, & Shapiro, 2013). It will be valuable to explore the role of foreign firms that are located in an industrial cluster in the product innovation of domestic-based cluster firms. Finally, we follow perceptions that see external search channels as separate search spaces (Laursen & Salter, 2006; Scott & Brown, 1999). That approach is limited because it does not allow analysis of the importance of the breadth and depth of local and nonlocal searches within each individual search channel. Future research should further explore the influence of the breadth and depth of each channel. Also note that we did not examine the role of each of the local and nonlocal knowledge sources. We expect that knowledge from different sources such as local customers, local suppliers, nonlocal research institutes, and nonlocal service intermediaries may affect cluster firms' product innovation in different ways and to different degrees. Future research should explore the influence of different knowledge sources on cluster firms' product innovation.

CONCLUSION

Our study explores the effects of local and nonlocal geographic searches on product innovation in industrial cluster firms by differentiating the depth dimension from the breadth dimension of geographic searches. It shows that local search breadth, local search depth, and nonlocal search breadth play positive roles, but nonlocal search depth plays no positive role in the product innovation of cluster firms. Moreover, both relative local search depth and relative nonlocal search breadth play significant roles in cluster firms' product innovation, and they contribute more to product innovation in stable industries than in dynamic industries. Our findings contribute to the literature on knowledge search and its role in cluster firm innovation, and suggest important implications for the knowledge search management of cluster firms.

NOTE

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