

External Heterogeneity in Open Innovation and Its Impact on Innovative Performance

Abstract

While current research commonly finds there may be an optimum overall level of search depth commitment at the apex of an inverted U relationship, it says comparatively little about the optimal allocation of search depth *between* competing search channels. Neither does it explore in depth the qualitative differences in the *breadth* of different external search channels. Here we conceptually and empirically explore the idea of the intra-search channel allocation problem using the concept of heterogeneity in search *depth* and *breadth*. We explore how variations in the distribution of open-innovation search *depth* and *breadth* influence innovation performance and in doing so contribute to a more fine grained conceptual understanding of external innovation. We do so an emerging market context, namely China. Our contributions are therefore twofold, involving both conceptual and empirical elements.

Keywords: open innovation; external innovation factors; heterogeneity, innovation performance

Introduction

Chesbrough's (2003) concept of 'open innovation' has been widely accepted in academic and business circles and 'closed innovation' is increasingly seen as inadequate for the demands of modern enterprise (Chen et al., 2008). Open innovation allows enterprises to use and exploit heterogeneous knowledge sources dispersed internally and externally. Current research on open innovation concentrates on factors influencing open innovation performance (Dahlander & Gann, 2010; Huizingh, 2011). The concept of the *degree* of openness has been used also to help breakdown the role of internal and external knowledge sources used during innovation processes, as well as the utilization levels of different kinds of knowledge sources. Laursen and Salter (2006), for example, systematically measured concepts known as the *depth* and *breadth* of open innovation and their impact on innovation performance. Others have subsequently further developed these ideas, introducing more sophistication in the understanding of *breadth* and *depth*, including concepts such as the *orientation* of open innovation (Chen et al., 2011; Chiang & Hung, 2010; Garriga, Krogh, & Spaeth, 2013).

The concept of the *degree* of open innovation, however, arguably only measures one aspect of the selection of external innovation channels in open innovation processes, namely the extent of co-operation between an enterprise and other external innovation sources or channels. They have usually done so in terms of the constructs

depth and *breadth* (Laursen & Salter, 2006). Previous studies have not yet, to the best of our knowledge, significantly concerned themselves directly with the issue of the qualitative heterogeneity and differentiation between the sources or channels of external innovation or the possible influences of this *differentiation* on innovation performance. As a recent review of the open innovation literature has noted: ‘research could benefit from concentrating more explicitly on the particular nature and context of external sources of innovation’ (Dahlander & Gann, 2010: 705). These factors also likely play an important part in the success or otherwise of open innovation (Huizingh, 2011). Furthermore, the construct of open innovation search *depth* has not accounted for how firms look to vary their allocations of commitment *across* different open innovation channels (what we refer to as the open innovation intra-search channel attention allocation problem). Or, as Laursen and Salter (2006) explain it in their seminal work, their definition of depth considers only the extent to which firms draw ‘deeply’ from outside sources. Comparatively little attention, therefore, has been paid to how depth is allocated *between* different search channels or of the wider spectrum of search depth commitments that firms may show to open innovation partners. Our contribution here, therefore, is to further explore how the impact of such things as variance in allocation of search depth impact innovation.

To address these conceptual and empirical gaps we introduce the concept of *heterogeneity* in the depth and breadth of external innovation sources, with the aim of

measuring the impact of the differentiation (or variance) in the allocation of search depth between partners in the process of open innovation, as well as how qualitative heterogeneity in search partners' technological levels influences innovation performance. We also, therefore, look to explore the ways in which an enterprise manages the heterogeneity in the technological levels of its open innovation partners. Thus we develop measures of heterogeneity in the depth and breadth of the search channels, building from recent work in this area (Chen et al. 2011; Laursen and Salter; 2006). To our knowledge, no studies have yet explored the intra-search channel allocation problem in this way. A further novel contribution we make is to undertake empirical testing of our ideas applied to the context of a large emerging market economy, namely China.

Conceptual background

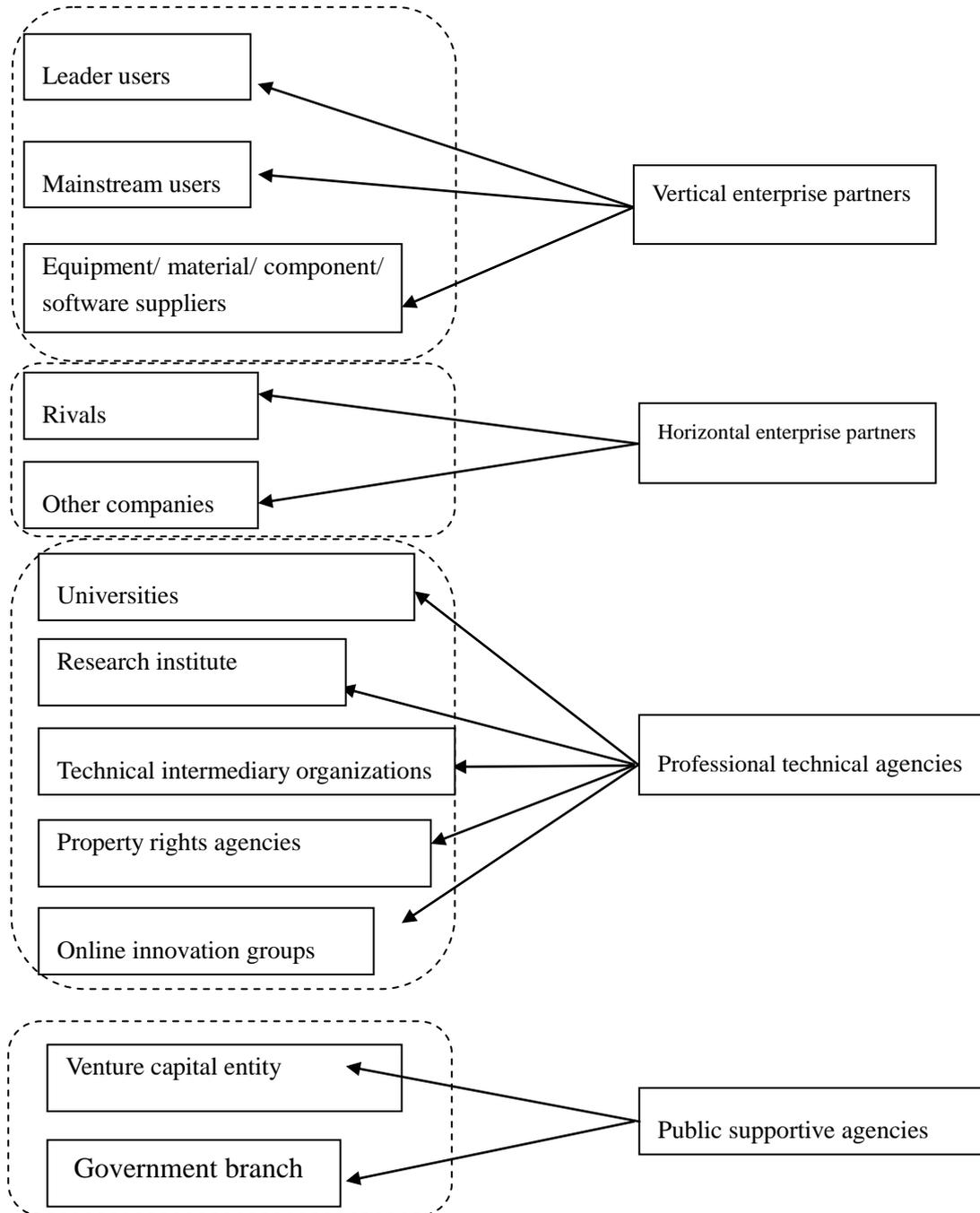
The concepts of *breadth* and *depth* of open innovation have been widely used and are considered as the 'two components of the openness of individual firms' external search strategies' (Laursen and Salter 2006: 131). External search breadth, is defined as 'the number of external sources or search channels that firms rely upon in their innovative activities' and external search depth 'is defined in terms of *the extent to which firms draw deeply from the different external sources or search channels*' (Laursen and Salter 2006: 134). Together the two variables have been considered to represent the openness of a firm's external search processes. We now discuss in more

detail the idea of *heterogeneity* in both the breadth and depth of open innovation sources.

Depth of open innovation and the intra-search channel allocation problem

Innovation sources can be divided into internal and external sources (Chesbrough, 2006). The former mainly include the internal R&D departments and staff of other departments; the latter include lead users, mainstream users, equipment/material/component/software suppliers, competitors, other enterprises (including those from industries), universities, research institutes, technology intermediary organizations, property rights agencies, online innovation communities, and government departments (see Figure 1).

Fig. 1: External innovation search channels



Search depth is generally understood as the extent to which firms draw ‘*deeply*’ from these channels (i.e the left hand boxes in figure 1) (Laursen and Salter 2006: 134). Yet fully capturing and understanding the concept of search depth is not necessarily straightforward, at either the conceptual or empirical level. This is because open search depth has usually been understood as the extent of the total commitment to open innovation channels, whereas comparatively little attention has been given to how firms allocate this total commitment *between* competing open innovation search channel partners. Yet, arguably, this is a key challenge facing the innovation processes of most businesses. To further illustrate the conceptual difficulties of understanding the open innovation intra search channel depth allocation problem it is probably simplest to first consider how measurements of open search depth have been operationalized. Laursen and Salter (2006) (hereafter LS), for example, in their seminal work (which has been followed by others (Chen, Chen, & Vanhaverbeke, 2011; Chiang & Hung, 2010)), use an additive composite indice. They look at 16 different sources of knowledge (i.e akin to the left hand boxes in figure 1) and each of the 16 sources are coded with 1 when the firm in question reports that it uses the source ‘*to a high degree*’ and 0 in the case of no, low, or medium use of the given source’ (Laursen and Salter 2006: 134). As in the case of their *breadth* variable (to which we turn next), the 16 binary variables for open innovation sources are subsequently added up, so that each firm gets a score of 0 when no knowledge sources

are used to a high degree, while the firm gets the value of 16 when all of the channels are drawn from to a high degree.

One possible conceptual and empirical issue with this binary approach, however, is that it does not explore in any detailed manner the underlying heterogeneity or variance in the search depths across the 16 different external search channels. In other words, it focuses on just high or low scores and the overall *extent* of external search depth commitment. In this regard, the binary variable approach may be rather crude in capturing the variance of the distribution in the way in which depth is allocated between channels. In reality the heterogeneity (or variance) in commitment to different search channels is likely to also be an important and complex decision making process businesses face, one that may also be central to the innovation process itself. Ideally, this intra-search channel allocation problem could be further studied using a more finely honed and sensitive measurement of *depth*. In reality firms face complex trade-offs between deciding not only which channels to invest in, but *how much* to invest in these competing and different channels. Firms must also constantly respond to the changing internal and external environment to reallocate their attention accordingly. If, therefore, we were to adopt a more fine-grained approach to the analysis of search depth we could get a clearer sense of how firms allocated their search depth *across* the different competing search channels.

We can think of this as an *intra*-search channel allocation problem, in which, given a certain overall level of commitment to external search depth (ideally at the apex of the commonly found inverted U), the firm is trying to maximize its returns from different external channels each of which has varying potential to facilitate innovation processes. This will entail careful and active management in the selection of the depth of its search channels, in which some channels receive greater investment and others less, depending upon their latent potential and the ability of the focal firm to exploit it. It is most likely the challenge of allocating depth efficiently will give rise to considerable heterogeneity in the distribution of search depth allocation across the different channels available. The nature of this challenge and way a firm chooses to solve the intra-search channel problem may also vary according to specific industry characteristics of the firm. The binary approach commonly used to measure search depth may not capture this intra-search channel allocation problem particularly well, or the large number of possible permutations in the variance of the distribution of search depth.

To illustrate this idea in more concrete terms we can use a simple numerical example. Instead of using the 0 or 1 binary variable of Laursen and Salter (2006), for example, we could employ a 7 point scale to measure search depth (with 7 being the maximum search depth). If we take the case of a score of say 5 in the Laursen and Salter (2006) approach (i.e 5 of 16 channels are used to a 'high degree') and further

assume, for the sake of simplicity, that a binary result of 1 corresponds to a score of say 7 on our alternative scale for a ‘high degree of commitment’, this would give us an aggregate score of 35 (out of possible total of $16*7 = 112$). Firstly, using the 5 scored in the LS binary approach would tell us nothing about the search depth commitments of the other 11 channels, as these would be bracketed within the ‘o’ score using the binary variable. So we could be losing potentially important information about lower levels of commitment (which could still be important) to other channels. In reality, for example, commitment of depth to these 11 channels could range considerably, and using our 7 point scale we could capture this (using say the 1-6 range). In theory, therefore, using this more detailed approach, a firm could still score a comparatively high level of depth (i.e $6*11 + 35 = 101$) while still showing apparently low overall levels of depth when using the less refined binary approach (i.e. as in LS model).

More importantly, however, for the point we wish to explore here, the LS approach tells very little about the distribution of the search depth allocation or commitment of the firm across the varying external search channels (i.e. the intra search channel allocation of depth). These allocations, for example, could be very much skewed in some cases but far more evenly distributed in others. To illustrate, if we assume that instead of having the previously mentioned search depth commitment of 6 to the 11 other available external search channels the firm instead had one of 3,

our total search depth score would come to 68 (i.e. $3*11 + 35 = 68$). Yet this search depth score could mask a huge range of possible permutations in search depth allocation for the 11 different search channels. For example, 5 of them could score 1, 5 of them 5 and 1 of them 3 (i.e. $(5*1) + (5*5) + (1*3) + 35=68$). The point to note here, using this simple numeric example, is that the operationalization of search depth, as it is currently conceived and utilized at an empirical level, tells us nothing about the *variability* in the distribution of intra-search channel depth. We call this *heterogeneity* or *variance* in search depth. The nature of the distribution in the search depth allocation, we argue, may be as important, if not more so, than the actual overall aggregated search depth *level*, the focus of much recent study. Indeed, in practice, innovating firms are likely to be not only concerned with their *overall* search depth (and where the inverted U point may lie for them), but also with the way in which they allocate their limited resources to different search channels within the framework of an overall *level* of commitment. So this can be seen as the intra-search channel *depth* allocation problem, one that all firms face whilst innovating.

Building from this idea, normal search depth is generally associated with improved innovative performance, yet ‘over-search’ will have negative consequences (i.e. there are diminishing returns). This is because, for example, there may be too many ideas for the firm to manage and choose between (‘the absorptive capacity problem’), as well as innovative ideas coming ‘at the wrong time and in the wrong

place to be fully exploited ('the timing problem')' (Laursen and Salter 2006: 135). Further, since there are so many ideas, few of these ideas are taken seriously or given the required level of attention or effort to bring them into implementation (the attention allocation problem). We will later consider how *heterogeneity* in search depth may influence some of these problems associated with excessive search depth.

Qualitative differences in search 'breadth' and their heterogeneity

The *scope* (Chen et al. 2011) or otherwise sometimes also known as *breadth* (Laursen and Salter, 2006) of open innovation channels refers to the number of types of different open innovation partners with which the innovating firm is interacting in open innovation processes (i.e the number of different left hand boxes in figure 1). The idea of heterogeneity of breadth in external innovation sources that we use here refers to the degree of differentiation between the external innovation sources used for open innovation. This is embodied not only in 'quantitative' aspects (i.e the number of different types of channels), which is the focus of many studies (Garriga et al., 2013; Laursen & Salter, 2006) but also in the actual 'qualitative' aspects of difference.

As Dahlander and Gann (2010: 707) note, there are risks associated with 'being pre-occupied with exploring the optimal level of openness rather than probing how openness has changed in a qualitative sense. Perhaps openness is today taking

different forms than in the past'. Chen et al. (2011), for example, addressing this idea, show how the '*orientation*' of open innovation channels can also make a difference to innovation performance. They look at DUI and STI related innovators and show how orientations towards different search channel types (vertical, horizontal etc.) has different impacts in different types of innovation processes. In effect, they go beyond breadth alone to explain performance. For example, while standard measures of breadth may show that two businesses from DUI and STI industries have equal levels of breadth, each may be drawing from very different types of channels (STI from universities, for example, DUI from suppliers and the like). Thus their orientations may be considerably different for any given level of *breadth*. There may also, of course, be a very wide range of other qualitative differences between these partners. In other words, *breadth* as it is currently operationalized only captures certain elements of a firm's open innovation strategies.

Building from this, it would be useful to have a more explicit and detailed insight into the impacts of qualitative differences between different search channels. Here we look to further refine the idea of breadth by introducing an explicit measure of heterogeneity in breadth regarding technological differences in open innovation partners. Heterogeneity in breadth, we argue, is related to the degree of differences in the qualitative aspects of the open innovation channels, such as those related to different industrial sectors, technological fields and the organizational nature of the

external innovation sources. These differences exist not only in comparison to the enterprise itself but also, more importantly, with regards to the differences between the external search channels themselves.

To summarize, LS have noted 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*’ (Laursen and Salter 2006: 133). We could also add to this that the degree of interaction *between* different existing search channels is also underexplored in this approach. The idea of heterogeneity of breadth therefore refers to the *differentiation* in qualitative aspects of industrial sectors, technological fields and organizational features between the external innovation channels.

Application of heterogeneity in breadth and depth to STI and DUI

The diversity and depth of a firm’s external sourcing relations on its innovative performance will also be contingent upon the industry to which the firm belongs. (Chen et al. 2011). Different industrial characteristics influence how external innovation sources are drawn from. In this paper, following Chen et al. (2011), we divide industries into science and technology-driven (STI) industries and experience

by doing, using and interacting (DUI) driven industries. STI industries refer to those dominated by scientific and technological knowledge as the basis for the innovation process, including industries such as those related ICT, computer services and software industries, bio-pharmaceuticals industry and space industry, and the like. DUI industries, by contrast, refer to those with know-how accumulated induring user processes, including traditional manufacturing industries (like textiles, apparel and the food industry) (Jensen, Johnson, Lorenz, & Lundvall, 2007). STI industries typically engage more in research and development (see figure 2).

From the perspective of resource-based theory, STI enterprises with stronger absorbtive capabilities should be able to better obtain benefits from heterogeneous external innovation sources. Enterprises in the DUI industries, by contrast, do not conduct much basic research of their own. They are more dependent on interaction with users and suppliers, finding solutions to problems by cooperating with other enterprises within or beyond their own industries, establishing more alliances with universities and R&D institutes when compared to STI industries in order to obtain market information resources, technological resources and manufacturing abilities. The innovation of DUI industries mainly relies on the experience of staff and users with critical know-how. Tacit knowledge, asset specificity and experience will spontaneously influence the stickiness of knowledge, and further influence the effects of knowledge transfer (Simonin, 1999). Therefore, in terms of DUI industries, greater

heterogeneity of external innovation sources may, in general, lead to better innovation performance.

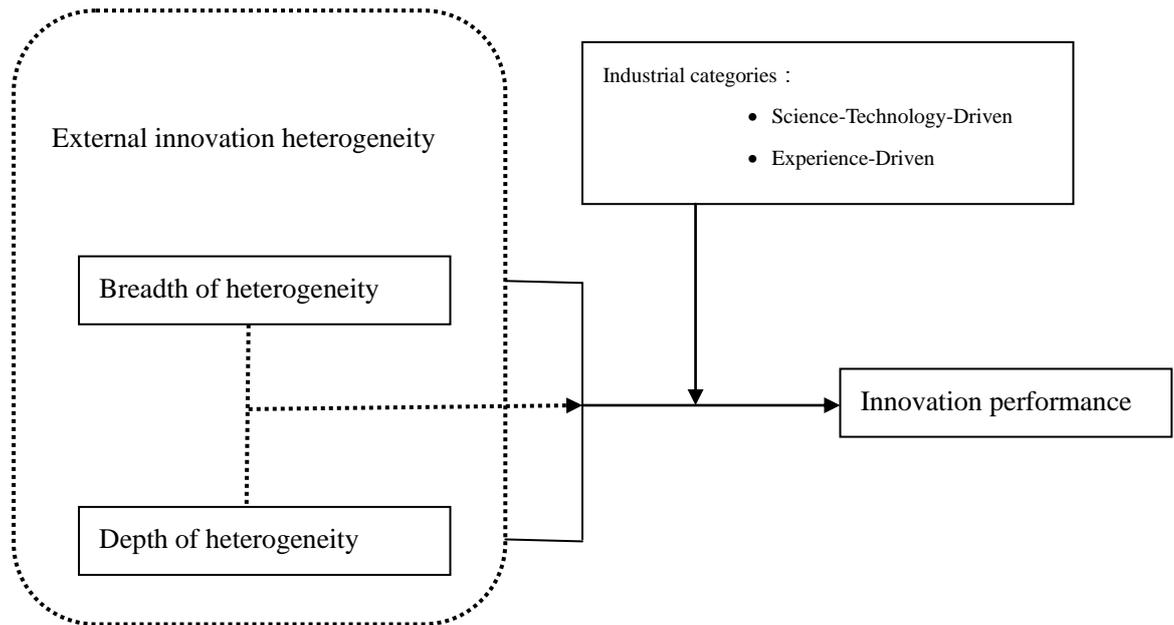


Fig. 2 Conceptual model of external innovation heterogeneity on innovation

For enterprises from STI industries, co-operating with innovation partners across varied technological fields may be unhelpful. This is because it draws greatly on their available resources and stretches their absorptive capacity. Focusing on a broader range of search channels and extending their scope but within similar technological fields will be more advantageous for them.

H1a: *For enterprises in technology-driven industries (STI), the greater the heterogeneity in the technological breadth of external innovation sources, the worse the innovation performance.*

It is generally argued that the ‘attention allocation problem’ is the key element in attention-based theories of the firm (Simon, 1947; Ocasio, 1997, c.f. Laursen and Salter, 2006). This theory suggests that managerial attention is the resource of greatest value inside the organization. The decision to allocate attention to particular activities is therefore a key factor in explaining innovation success. Central to this approach is to ‘highlight the pool of attention inside the firm and how this attention is allocated’ (Laursen and Salter 2006: 135). According to the theory, decision-makers need to ‘concentrate their energy, effort and mindfulness on a limited number of issues’ in order to achieve sustained strategic performance (Laursen and Salter, 2006: 135). Consequently, the theory suggests that ‘a poor allocation of managerial attention can lead to firms engaging in too many (or too few) external and internal communication channels’ (ibid.). We can, of course, directly extend this line of thinking to heterogeneity of search depth. For example, not all external innovation partners will warrant the same attention, but they may still warrant *some*. Greater heterogeneity in search depth, therefore, may reflect greater sophistication in how a firm draws from external search channels. However, there may also be threshold levels, with too little attention or too much attention (at the level of the individual

search channel, i.e. vertical collaborator etc.) yielding poor innovation returns. In the former case, limited attention may make it impossible to effectively draw from the channel. In the latter, excessive attention simply leads to diminishing returns. In other words, it is not just the absolute levels of open innovation depth that matter, it is also how firms allocate their search efforts across the various open innovation channels that they have found.

H1b: *For enterprises in technology-driven (STI) industries there is an inverted U-shaped relationship between the heterogeneity of depth of the open innovation channels and innovation performance.*

Are there any interaction effects between heterogeneity of breadth and depth? Greater heterogeneity in breadth (H1a), it could be argued, will also require greater attention (i.e. depth) to the more technologically different search channels. With an expansion in the different types of technological fields (heterogeneity of breadth) incorporated in external search channels, firms will have to be far more selective in which search channels they invest in. Thus there may be a complementary between the two, up to a certain point. With growing variation in breadth there is a far greater requirement for STI businesses to be selective – i.e. more time must be spent on some projects and far less on others.

H1c: *For enterprises in technology-driven (STI) industries there is a complementary relationship between the external heterogeneity of breadth and heterogeneity of depth.*

Similar to STI, DUI enterprises will also find it difficult to exploit excessive heterogeneity in technological breadth.

H2a: *For enterprises in the experience-driven (DUI) industries the greater the heterogeneity in technological breadth of external innovation sources the worse the innovation performance.*

Unlike STI, DUI enterprises may cope better with heterogeneity in depth. DUI requires less firm-level absorptive capacity and in general DUI will be more predisposed toward greater breadth, as: ‘firms that score high on open search breadth access knowledge from a large number of external sources and thus conduct broader and more general knowledge searches’ (Chiang and Hung, 2010: 293).

H2b: *For enterprises in the experience-driven (DUI) industries, there is a positive relationship between the heterogeneity of depth of the external innovation factors and innovation performance.*

Data and methodology

The context for our empirical testing is China. As Huisingh (2011) has noted, further large-scale empirical verification of open innovation ideas is required in different contexts. We use a questionnaire survey of managers asking them directly about the sources of heterogeneity in their open innovation strategies. This approach allows us to ‘examine the nature of external search strategy, highlighting the range of choices firms make about how best to exploit external sources of knowledge’ (Laursen and Salter 2006: 134). We also develop a measure of heterogeneity drawing from approaches used in different fields.

The concept of heterogeneity has received significant attention in strategic management and HRM fields (O’Reilly, 1989; Watson, 1993). On the one hand it is used, for example, to describe the unique resource endowment of an enterprise and on the other the degree of differentiation in demographics between members in a group or a team (called *team heterogeneity*). Regarding the influence of heterogeneity on team efficiency, most evaluations hold that heterogeneity may be a ‘double-edged sword’. The presence of heterogeneity may promote a team to propose high-quality resolutions but it may at the same time reduce team cohesion and bring about conflicts (Watson, 1993). Scholars have used different ways to measure the degree of heterogeneity on the basis of different research directions and the characteristics of

heterogeneity under consideration (O'Reilly, 1989). In terms of the heterogeneity of top management teams, however, two major methods can be adopted. One is to measure the coefficient of variation (Allison, 1978), which has also been used to analyse questionnaire data, such as that related to the heterogeneity of team culture. Here we focus on the heterogeneity of external innovation sources in open innovation using the coefficient of variation (hereafter CV), which is the ratio of the standard deviation to the mean:

$$c_v = \frac{\sigma}{\mu}$$

This coefficient's main advantage is that it is dimensionless and is used for comparisons between data sets with different units of measurement or different means. It provides, essentially, a comparable measure of variance in the distribution of the external *breadth* and *depth* of open innovation (i.e. what we call heterogeneity or variance). It therefore provides insights into the heterogeneity in the degree of cooperation between enterprise and the twelve innovation sources (depth) as well as the variation in their *breadth*.

In order to test our hypotheses we used questionnaires asking respondents about the number of external innovation partners which had cooperative relationships with the enterprise, their frequency and duration of cooperation. The questionnaire was

based on a 7-point Likert scale (thus being similar to our previous discussion of heterogeneity of breadth and depth). To operationalize our measure of breadth we also asked: ‘how different do you think your company’s technological field is from the following 12 collaborators’ (i.e. see figure 1) and took its coefficient of variation as our measure of heterogeneity in search breadth.

Systematic examination of the hypotheses in this study was conducted through the steps of small-scale pre-test, modification and improvement, followed by large-scale distribution, collection, collation, data sorting and analysis. The survey was conducted in Zhejiang, Shanghai and Beijing in the vicinity of science and technology-driven industries (including chemical, electronics, bio-pharmaceutical and software industries) and experience-driven industries (such as textile and garment industries and the like). It also involved field interviews supporting the questionnaires (Table 1).

Valid data from the returned questionnaires was statistically analyzed and the impacts of heterogeneity in external innovation sources, vertical and horizontal cooperative enterprises, specialized technical institutions and public support structure on open innovation performance were analyzed. In terms of industrial distribution of respondents, samples were limited to technology-driven industries (such as the chemical, electronic, bio-pharmaceutical and software industries), as well as experience-driven industries (such as the textile and garment industry).

Respondents were required to meet the following conditions: more than three years employment in the enterprise; good understanding of the enterprise's main products/services and innovation process; and participation in the enterprise's cooperation with external organizations. As a result, most respondents were experienced employees and came from higher level management and marketing positions.

Table 1: the distribution channels and recycling statistics from questionnaires.

Channel	Distributing Quantities	Recycling Quantities	Effective Quantities	Recycling Ratio/%	Effective Ratio/%
Site Interviews	36	28	26	78	93
Network distribution	220	120	75	55	63
Total	256	148	101	58	68

In this study, Zhang and Li (2010), et al.'s measure of innovation performance is used as the dependent variable, namely: the annual number of new products or services, proportion of sales revenue from new products/services developed in the last two years to total sales revenue, and speed of new product/service development. The independent variables include the heterogeneity of external innovation (i.e. Figure 1) as measured by the coefficient of variation (CV). The breadth of technological heterogeneity refers to the degree of differences in qualitative aspects such as industrial sectors, technical fields and organizational nature of the external innovation

sourcess compared to the focal enterprise (measured by CV). The ‘depth of heterogeneity’ is measured by the quantity of external innovation factors and their communication duration and frequency with the enterprise (see table 2). There are therefore three explanatory variables in this paper, heterogeneity of breadth and depth sources and the interaction of breadth and depth. A number of control variables, following other studies, are also used (Table 3). These include: firm size (total number of employees); length of establishment (number of years of operation); and firm growth rate. Larger and older firms are expected to have better innovation performance owing to the accumulation of more resources and experience.

Table 2 Items related to the heterogeneity of external innovation factors

Name of variables	Items of measure
heterogeneity in technological breadth	Differences in technological field, as measured by coefficient of variation (cv)
Depth of heterogeneity of external innovation sources	Frequency of access to information
	Length of time for maintaining business contacts
	Number of external innovation factors with which relations are Established. All CV.

The reliability and validity of the questionnaire data were tested. Correlation analysis and multiple linear regression were used to explore the influence of *heterogeneity of technological breadth* and *depth* and their interaction on innovation

performance. The surveyed enterprises range from 30 to 8,000 employees (with an average of 2,830). The phase of the enterprise, the dominant industrial classification and its age were analysed. The Cronbach α for the twelve external innovation sources met the accepted 0.6 threshold. In addition, the three items of innovation performance were validated.

Multicollinearity, heteroscedasticity and serial correlation were tested for. The Variance Inflation Factor (VIF) stood between 1 and 10, indicating no issues. To test for heteroscedasticity, scatter-diagrams with standardized expected values on the X axis and standardized residuals on the Y axis were calculated, again these indicated no remedial issues were necessary. Before undertaking the regression analysis, the three control variables, three explanatory variables and one explained variable, correlation analysis was used to examine their correlation after standardization. This is significant between the explained variable (innovation performance) and the explanatory variables (the heterogeneity breadth of external innovation sources) ($p < 0.01$).

Results

Table 3 reports the results of our multivariate analysis on firms' innovation performance and heterogeneity in depth and breadth in the STI industries. We first regress firms' innovation performance on our control variables. As expected, in Model

1 larger and older firms ($\beta=0.338$, $P<0.01$, $\beta=0.560$, $P<0.01$) had better innovative performance (the control variable 'Employees' is significantly positive in all our models). In model 2 we introduce our main explanatory variables. The coefficient for heterogeneity of breadth is negative and statistically significant ($\beta=-0.880$, $P<0.01$). This result is also significant throughout models 1-5. This supports H1a that firms with a greater heterogeneity in the technological breadth of external innovation partners lower its innovation performance. Heterogeneity of depth is positive and significant ($\beta=0.190$, $P<0.01$). This result is robust at the 1% significance level across all models. In model 3, we include the quadratic depth term and it is significant but negative ($\beta=-0.160$, $P<0.05$). In model 4 we include the interaction term between depth and breadth and find depth significantly negatively moderates the negative relationship between breadth and innovation performance. Finally, in the full model the interaction variable between the quadratic term of depth and the breadth variable are included. The results indicate a significant and positively non-linear moderating effect, showing a curvilinear effect of depth. The inclusion of these variables shows an increase in explanatory power from model 1 (modulated $R^2=0.434$) to model 5 (modulated $R^2=0.987$).

Table 3 Multivariate regression analysis results for STI industries

Variables	M1	M2	M3	M4	M5
Employees	.338***	.149***	.139***	.102***	.054**
Period of establishment	.560***	.171***	.158***	.003	-.012
Stage of development	.091	-.049	-.032	-.002	.017
Heterogeneity of depth		.190***	.210***	.520***	.444***
Heterogeneity of breadth		-.880***	-.756***	-.957***	-.996***
Heterogeneity of depth ²			-.160**	.093*	-.239***
Heterogeneity depth× heterogeneity breadth				-.431***	-.395***
(Heterogeneity depth) ² ×heterogeneity breadth					.379***
Model statistics					
R ²	0.471	0.917	0.926	0.979	0.99
Modulated R ²	0.434	0.907	0.915	0.975	0.987
F statistics	12.745	90.423	83.816	257.962	449.897

Note: the figures in the table are standardized regression coefficient; * indicates p<0.10; ** indicates p<0.01; and ***indicates p<0.001.

In table 4, we repeat the process for our regression as in table 3. In our full model 3, we find that quickly growing companies in the DUI industries have better innovation performance ($\beta=0.049$, $P<0.10$). We introduce our main effect of both the depth and breadth in model 2. Depth is positive and significant ($\beta=0.606$, $P<0.01$) while breadth is significantly negative ($\beta=-0.444$, $P<0.01$). These results suggest that in DUI firms

with greater heterogeneity in technological breadth have lower innovation performance, while those with greater depth have higher performance. These results support both H2a and H2b. We also find breadth significantly and negatively moderates the positive relationship between depth and performance ($\beta=-0.221$, $P<0.01$).

Table 4 Multivariate regression analysis results----DUI industries

Variables	M1	M2	M3
Employees	-.079	-.041	-.026
Establishing period	.011	.046	-.009
Developing stage	-.076	-.005	.049*
Heterogeneity depth		.606***	.406***
Heterogeneity of breadth		-.444***	-.669***
Heterogeneity depth× heterogeneity breadth			-.221***
Model statistics			
R ²	0.014	0.974	0.987
Modulated R ²	-0.049	0.971	0.985
F statistics	.221	336.944	565.850

Discussion

STI enterprises and heterogeneity of depth and technological breadth

While a greater number of open innovation channels (i.e. standard breadth) may be positive for innovation performance (Chen et al, 2011; Laursen and Salter, 2006), our results show that increased heterogeneity (i.e. variation) in the technological fields of the different external search channels that STI businesses draw from is not necessarily good for innovation performance (supporting H1a) in Table 3. This implies STI businesses require focused attention on the specific technological fields of external innovation channels and should be wary of drawing from excessively heterogeneous innovation partners (and possibly, although we have not tested for this, it is interesting to consider whether they should also engage with partners of broadly similar technological capabilities). However, our results also suggest that greater heterogeneity in the extent to which STI businesses deeply engage with innovation partners (i.e. heterogeneity of depth, H1b) can also improve their overall innovation performance. We interpret this as meaning that not all open innovation partners offer the same opportunities for innovation success. Thus STI businesses must be discerning, lavishing more attention on the innovation channels they perceive to be more promising and expending fewer energies on those with less potential. This suggests that one of the key elements in successful open innovation strategies for STI businesses is their ability to discern the potential of their innovation partners and respond accordingly (in terms of their commitment to the channel). This, as we noted earlier, is related to the ‘attention allocation problem’. What we are specifically looking at here is the intra-search channel allocation problem. As noted, this is

somewhat different from the typical idea of search depth, which refers to the overall level of optimum engagement with external channels. Typically, it is argued, this experiences diminishing returns, owing to various factors, including the attention allocation problem.

What our results show is that as well as having sufficient absorptive capacity to engage with external partners, sufficient refinement in the allocation of resources between existing search channels must be achieved. It suggests that stronger commitment must be made to certain strategic investments, while others, potentially less rewarding external search channels, should be given less attention (i.e. leading to a higher CV for the distribution of external search depth). It is, therefore, not simply enough to be committed to a wide *breadth* of search (i.e. ideally to the point at which the apex of the inverted U-curvilinear relationship is found) but also to be discriminating in how these different open innovation channels are drawn from. This is because our sample also shows (as in other research, i.e. Chen et al. (2011); Laursen and Salter (2007)) that while the *variation* in depth is important to improving performance, in terms of total, overall commitment (i.e. standard search depth) the usual inverse relationship also applies (i.e. depth^2 is negative). In other words, there are diminishing returns to *overall* search depth, owing, for example, to limited managerial and absorptive capabilities, and that the way in which these open innovation channels are drawn from is vital to overall innovation performance. Firms must be discerning, in other words.

Finally, we find that although variation in the technological breadth of open innovation search channels in general has a negative impact on innovation performance this can be tempered by increased depth. Intuitively this can be interpreted as implying that increased heterogeneity in technological breadth requires the innovating firm to pay far greater attention to the intra-search channel allocation problem. Engaging with a broader range of external technologies it will be found that some require far greater search investments if their full potential is to be realized. Thus, while in general greater heterogeneity of technological breadth is a bad thing, there are strategies that firms can employ to counter the negative impacts of excessive heterogeneity at this level.

DUI enterprises and heterogeneity of depth and technological breadth

Our results for DUI also show that greater variation in the technological fields of the external search channels from which DUI businesses search have a negative impact on innovation performance, although the extent of this negative impact appears less than for STI businesses (in line with the idea that DUI is experience based)(see Table 4). Again, this negative impact may not be entirely unsurprising. Previous research on open innovation channels for DUI shows that increased scope of external search channels may be positive (Chen et al. 2011). Here, however, we are also accounting for

the variation in the technological fields of these external channels. Variation in the different technological fields may lead to excessive diversification in innovation strategies. As a result, innovators may find it hard to deal with the increased complexity of engaging with a range of different external innovation partners. Similar to STI industries, moreover, DUI industries must also make important choices about *where* they focus their open innovation energies within their existing available search channels. Greater variation in search depth again appears to have a positive impact on innovation performance. This most likely reflects the fact that not all external search channels harbour the same potential. Firms must make important decisions about where to focus their energies. Again, this finding is somewhat consistent with some earlier research, for example, which finds that greater diversity (or *scope*) in search channels is important. In this case, however, the diversity is not so much concerned with scope (or breadth as Laursen and Salter (2006) label it) but rather with the diversity in the depth of engagement with open innovation partners.

These findings on variation in search depth, it should be noted, are somewhat consistent with the findings that external search *orientation* (discussed earlier) also has can influence innovation.

Concluding comments

It has been noted that ‘research could benefit from concentrating more explicitly on the particular nature and context of external sources of innovation (Gassmann, 2006)’ (Dahlander and Gann, 2010: 705). Addressing this call and focusing on the ideas of heterogeneity or variance in depth and technological breadth, our original contribution to the literature here is to attempt a preliminary exploration of how heterogeneity in both *breadth* and *depth* affects innovation. Specifically, we have analysed the impacts of heterogeneity of *technological breadth* and *depth* of external search on the innovative performance of firms. The importance of this latter concept, in particular, is that it considers the intra-search channel allocation problem. Most previous research, by contrast, has considered the optimum *overall level* of engagement with external search partners. While this research finds an inverted U-shaped relationship for overall search depth, our findings (for STI enterprises in particular) also suggest that there may be an inverted U-shaped relationship for the *intra search channel depth* allocation problem. In other words, as well as being discerning about the overall level of external engagement, firms must constantly be evaluating how they allocate their time and energy between competing existing search channels. This, as far as we are aware, is the first time the problem of intra-search channel depth allocation has been analysed in any detail, supported by empirical analysis.

Our empirical findings are still preliminary and do require further testing with both larger samples and in different contexts. Additional research in this area is necessary so as to better understand the nature of the innovation problem. Extensive analysis on the practical operation of open innovation, moreover, is still somewhat lacking (Huizingh, 2011). This has caused a gulf between the study of open innovation theory and its application in practice. Our findings here suggest that firms must not only consider the depth of engagement, but also the way in which this depth is organized. In other words, not all forms of open innovation depth are the same.

Further research could extend these ideas to samples of companies from the developed world and could look to develop more refined and sophisticated measures of search heterogeneity in depth and breadth. Our understanding of the interaction between the two, moreover, is still conceptually immature. This is in part owing to the lack of current research. We also have not tested for the extent to which firms in the STI industries are better off working with partners with broadly similar technological capabilities and in similar fields. In this regard, we are limited by our respondents' understanding of industry and technological classifications. Further studies could address this problem by improving the survey design. We also empirically test this research only in the context of China. Our study, furthermore, is based on a cross sectional survey with limited information collected to ensure the reliability of our explanatory variables. A longitudinal study could control for more unobserved effects.

Future studies may attempt to overcome these limitations and provide further empirical evidence to advance our understanding of this field.

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