TL 062

THE INFLUENCE OF OPENNESS TO INNOVATION PERFORMANCE: EMPIRICAL ANALYSIS BASED ON INDUSTRY CLASSIFICATION

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Abstract According to the propensity for open innovation, this paper divides the manufacturing industries into three sub-groups. Using a sample of 345 manufacturing firms, this paper empirically verifies the relationship between the degree of openness and the innovation performance in different industries. Results show that external search breadth and depth are all curvilinearly (taking an inverted U-shape) related to performance in each industries. For firms which are more fit with open innovation, their optimal external search breadth is wider and external search depth deeper.

Key words Open innovation; Innovation performance; Openness

1 Introduction

The task of managing innovation is vital for companies of every size in every industry. Through deeply research into meta-innovation, H. Chesbrough brought out the new innovation paradigm-open innovation in 2003. This paradigm offers a new way of thinking and managing about innovation. By leveraging inside and outside innovation resources, open innovation can speed innovation, reduce the uncertainty of technology and market. However, considering the searching costs, transaction costs and administrative costs, open will bring negative impacts on innovation performance. In addition, open may lead to leakage of internal technology and intellectual property dispute. “The more, the better” is not always true. The influence of openness to innovation performance is complex. The effect of implement open innovation is difference in different industries. These should be specifically treated rather than general. In this paper, we empirically verify the relationship between the degree of openness and the innovation performance in different industries, and providing some reasonable guidance for enterprises to advance the technological innovation capabilities.

Domestically and internationally, there is now growing interest in conducting research on aspects of open innovation. John (2002) noted that no company was smart enough to know what to do with every new opportunity it found, and no company had enough resources to pursue all the opportunities it might execute [1]. Rigby & Zook (2002) suggested that open innovation was a good way to raise cash and keep talent. Exporting ideas improved motivation and loyalty among employees. Exporting and importing ideas helped companies clarify what they do best [2]. Rothaermel et al. (2006) found that cutting edge knowledge necessary for innovation tended to be dispersed across different actors and actor groups [3]. Alfred (2007) said that open source development provided important management lessons regarding the most effective ways to structure and implement innovation [4].

Recently some scholars had been proved firms have a tendency to "over-search" through empirically verify. Katila & Ahuja (2002) found that a firm's innovative performances in part a function of its search behavior and that there was a curvilinear relationship—taking an inverted U-shape—between depth and scope on the one hand and innovative performance on the other [5]. Keld & Ammon (2006) examined the relationship between openness and innovation performance, this research was based on a statistical analysis of the U.K. innovation survey. Results show that searching widely and deeply was curvilinearly related to performance [6]. Chen, et al. (2006) researched on the relationship between the degree of openness and the innovation performance of firms in China, they also found this relationship [7].

Lichtenthaler (2008) found that firms with limited product diversification would rely on external technology exploitation to a higher degree. Moreover, firms with limited product diversification were likely able to internally develop the major part of their technologies [8]. Rigby & Zook (2002) point that companies can determine whether it is favorable or unfavorable for them to pursue open-market innovation by considering the business environment they are operating in, along five key dimensions: Intensity of Innovation, Economies of Innovation, Need for Cumulative Innovations, Applicability of Innovations Across Companies or Industries, Market Volatility [2].

In sum, all these studies point to the importance of open behavior by firms in their search for innovative opportunities, but too open will bring negative impacts. Some firms may have a tendency to "over-search". Recently, those empirically verifies researches on the influence of openness to innovation, all tread the firms in different industries as a whole, do not considered the tremendous impact of industry character to implement open innovation. This paper will classify the manufacturing industries, and then empirically verify the relationship between the degree of openness and the innovation performance in different industries.

Accordingly, the hypothesis of this paper can be stated as: Hypothesis 1: External search breadth is curvilinearly (taking an inverted U-shape) related to innovative performance. For firms which are more fit in with open innovation, their optimal external search breadth is wider. Hypothesis 2: External search depth is curvilinearly (taking an inverted U-shape) related to innovative performance. For firms which are more fit in with open innovation, their optimal external search depth is deeper

2 Research Method

The variable in this paper is the percentage of innovative sales and therefore by definition ranges between 0 and 1. Dependent variable values are Limited, so a Tobit analysis is applied.

The Tobit regression model, first proposed by Tobin in 1958, is intended for measures with censored data. The model supposes that there is a latent (i.e. unobservable) variable y_i^*. This variable linearly depends on x_i via a parameter (vector) β which determines the relationship between the independent variable (or vector) x_i and the latent variable y_i^* (just as in a linear model). In addition, there is a normally distributed error term u_i to capture random influences on this relationship. The observable variable y_i is defined to be equal to the latent variable whenever the latent variable is above zero and zero otherwise.

$$y_i = \begin{cases} y_i^* & if\ \ y_i^* \succ 0 \\ 0 & if\ \ y_i^* \le 0 \end{cases} \tag{1}$$

Where y_i^* is a latent variable：

$$y_i^* = \beta \chi_i + \mu_i\ ,\ \mu_i \sim N\left(0, \delta^2\right) \tag{2}$$

If the relationship parameter β is estimated by regressing the observed y_i on $x_{i,}$ the resulting ordinary least squares regression estimator is inconsistent. It will yield a downwards-biased estimate of the slope coefficient and an upwards-biased estimate of the intercept. Amemiya (1973) has proven that the likelihood estimator suggested by Tobin for this model is consistent[15].

The Tobit model is a special case of a censored regression model, because the latent variable y_i^* cannot always be observed while the independent variable x_i is observable. A common variation of the Tobit model is censoring at a value y_L different from zero:

$$y_i = \begin{cases} y_i^* & if\ \ y_i^* \succ y_L \\ y_L & if\ \ y_i^* \le y_L \end{cases} \tag{3}$$

Another model results when yi is censored from above and below at the same time.

$$y_i = \begin{cases} y_i^* & if\ \ y_L \prec y_i^* \prec y_U \\ y_L & if\ \ y_i^* \le y_L \\ y_U & if\ \ y_i^* \ge y_U \end{cases} \tag{4}$$

Such generalizations are typically also called Tobit model. Depending on where and when censoring occurs, other variations of the Tobit model can be obtained. Amemiya (1985) classifies these variations into five categories, where Tobit type I stands for the model described above [16].

3 Analysis and Results

3.1 Industry classification

According to the five core indicators brought forward by Righy and Zook (2002), combined with the data from Statistical yearbook of China, China statistical yearbook on science and technology, National survey of industrial enterprises innovation statistics in 2007 and State intellectual property office of P.R.C, used weighted averaging method, this paper divides the manufacturing industries into three sub-groups from the industry which is not suitable to open innovation to the industry which is very suitable to open innovation, the results are as following:

The first sub-group includes: 43 Recycling and Disposal of Waste, 19 Manufacture of Leather, Fur, Feather and Related Products, 18 Manufacture of Textile Wearing Apparel, Footware, and Caps, 28 Manufacture of Chemical Fibers, 20 Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products, 13 Processing of Food from Agricultural Products, 33 Smelting and Pressing of Non-ferrous Metals, 21 Manufacture of Furniture, 22 Manufacture of Paper and Paper Products, 17 Manufacture of Textile;

The second sub-group includes: 42 Manufacture of Artwork and Other Manufacturing, 25 Processing of Petroleum, Coking, Processing of Nuclear Fuel, 24 Manufacture of Articles For Culture, Education and Sport Activity, 34 Manufacture of Metal Products, 30 Manufacture of Plastics, 29 Manufacture of Rubber, 16 Manufacture of Tobacco, 32 Smelting and Pressing of Ferrous Metals, 14 Manufacture of Foods, 23 Printing, Reproduction of Recording Media;

The third sub-group includes: 31 Manufacture of Non-metallic Mineral Products, 37 Manufacture of Transport Equipment, 15 Manufacture of Beverages, 39 Manufacture of Electrical Machinery and Equipment, 41 Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work, 36 Manufacture of Special Purpose Machinery, 35 Manufacture of General Purpose Machinery, 40 Manufacture of Communication Equipment, Computers and Other Electronic Equipment, 26 Manufacture of Raw Chemical Materials and Chemical Products, 27 Manufacture of Medicines.

3.2 Data and variables

The research data is obtained through questionnaire. The survey is based on National survey of industrial enterprises innovation statistics in 2007 and divided external innovation sources into 11 categories. The survey was targeted at China's manufacturing industry. Each firm was asked to indicate on a 0-1-2-3 scale the degree of use for each source. A total of 655 questionnaires were issued, 345 valid questionnaires were received, a response rate of 52.7 percent. Respondents are technical supervisor or senior business managers. In these samples, 101 valid questionnaires were belonged to the first sub-group, 107 were belonged to the second sub-group, and 137 were belonged to the third sub-group. Descriptive statistics are given in Table1.

Table 1 Sources of Information and Knowledge for Innovation Activities (N=345)

Knowledge source	Percentages			
	High	Medium	Low	Not used
1. Clients or customers	34	37	16	13
2. Suppliers of equipment, materials, or components	27	36	21	16
3. Competitors and other enterprises in the same industry	21	40	15	24
4. Technology market or Consultants	14	33	15	38
5.Trade associations	10	31	18	41
6. Universities or other higher education institutes	8	23	24	45
7. Research institutes	11	27	23	39
8. Government organizations	10	29	25	36
9. Fairs, exhibitions	19	33	18	40
10. Scientific and technical literature	9	32	26	33
11. Internet media	15	36	22	27

Table1 presents the results for the entire range of sources for manufacturing firms. Overall, the results indicate that the most important source is clients and customers, followed closely by suppliers of equipment, materials, and components. Alongside customers and suppliers, a range of standards, such as competitors, fairs, exhibitions are among key sources of innovation. As might be expected (see von Hippel, 1988), the results indicate that firms' innovation activities are strongly determined by relations between themselves and their customers and suppliers in China.

Dependent Variable We use two proxies aimed at reflecting various types of innovative performance by firms. First, we use a variable aimed at indicating the ability of the firm to produce radical innovations. This variable is measured as the fraction of the firm's turnover relating to products new to the world market (performance1). Another variable for incremental innovation, measured as the fraction of the firm's turnover relating to products new to the firm (performance 2).

Independent Variables According to the research by Katila and Ahua (2002), Laursen and Salter (2006), the paper divided openness into two dimensions, "breadth" and "depth" to measure. BREADTH is constructed as a combination of the 11 sources of knowledge or information for innovation. As a starting point, each of the 11 sources are coded as a binary variable, 0 being no use and 1 being use of the given knowledge source. Subsequently, the 11 sources are simply added up so that each firm gets a 0 when no knowledge sources are used, while the firm gets the value of 11, when all knowledge sources are used. Although our variable is a relatively simple construct, it has a high degree of internal consistency (Cronbach's alpha coefficient = 0.82). DEPTH is constructed using the same 11 sources of knowledge as those used in constructing BREADTH. In this case each of the 11 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(Cronbach's alpha coefficient = 0.76).

3.3 Data analysis and results

3.3.1 Correlations among openness and innovation performance

We examine the correlations among breadth, depth and innovation performance. Using SPSS software calculated Pearson product-moment correlation result in Table 2. As predicted, breadth and depth were significantly related to innovation performance.

Table 2 Correlations Among Openness and Innovation Performance

Control Variable	Variable	breadth	depth	performance1	performance
Age, size	breadth	1.00			
	depth	0.46**	1.00		
	performance1	0.43 **	0.33*	1.00	
	performance2	0.26	0.23*	0.43*	1.00

One-tailed *t* -test applied , $^{+}$p<0.10; *p<0.05; **p<0.01; ***p<0.001

Table 3 Tobit Regression, Explaining Innovation Performance

Type	Model Dependent variables Independent variable	I		II	
		Performance I		Performance II	
		Coefficient	S.E.	Coefficient	S.E.
The first sub-group	BREADTH	.106*	.083	.106^{+}	.062
	BREADTH2	-.010*	.008	-.009	.004
	DEPTH	.182**	.040	.081**	.034
	DEPTH2	-.046 **	.009	-.019*	.008
The second sub-group	BREADTH	.128*	.047	.134*	.063
	BREADTH2	-.009**	.013	-.009*	.004
	DEPTH	.146*	.029	.063**	.023
	DEPTH2	-.021^{+}	.003	-.011*	.004
The third sub-group	BREADTH	.172**	.053	.179*	.063
	BREADTH2	-.010**	.003	-.010*	.004
	DEPTH	.028*	.019	.061**	.023
	DEPTH	-.003	.003	-.009**	.004

One-tailed *t* -test applied , $^{+}$p<0.10; *p<0.05; **p<0.01; ***p<0.001

3.3.2 Regression analysis the impact of openness on innovation performance

In Table 3, we find strong support for the hypothesis asserting that external search breadth and depth are all curvilinearly-taking an inverted U shape-related to innovative performance in three sub-groups. First, the parameter for external BREADTH is significant and positive for all degrees of novelty of innovation (performance1, performance2), showing that the breadth of openness of firms' innovative search is an important factor in explaining innovative performance. Second, the parameter for BREADTH squared is significant as well, showing that when firms use too many sources in their search for innovation there are decreasing returns. In the case of the influence of breath to innovations new to the world (performance1) in three sub-groups, we get Figure 1:

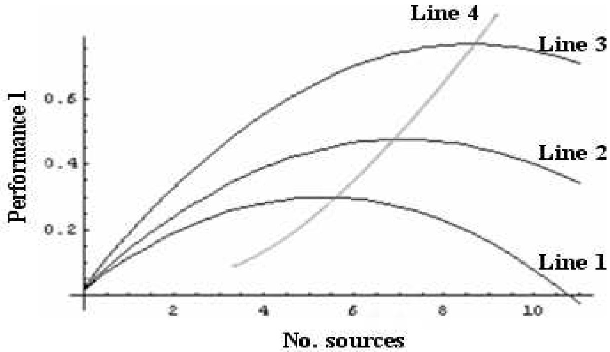

Figure 1 Predicted Relationship between Performance 1 and Breath in Three Sub-groups

Line 1, line 2 and line 3, respect the relationships between performance 1 and breath in three sub-groups. Connected three tipping point, we can get Line 4, which is slanting upward to the right. From Figure 1 it can be seen that, the 'tipping point' in Line 1 is at 5 sources, so that if firms in first sub-group use more than 5 sources of external knowledge for their innovative activities negative returns set in. The tipping point in Line 2 is at 7 sources and in line 3 is at 8-9 sources. This means for firms which are more fit in with open innovation, their optimal external search breadth is wider. Innovation performance and "depth" have the same relationship. The results give strong support for our hypothesis.

4 Conclusions

Using the five core indicators brought forward by Righy & Zook (2002), we divided the manufacturing industries into three sub-groups. According to the research by Katila & Ahua (2002) and Laursen & Salter (2006), we measured openness from two dimensions, "breadth" and "depth". Using Tobit regression model, we analysis the relationship between openness and innovation performance in each sub-groups.

The results of the Tobit regression analysis show that external search breadth and depth are all curvilinearly-taking an inverted U shape-related to innovative performance in three sub-groups. As the degree of openness increases, firm's innovation performance will increase, however, if firms use sources of external knowledge beyond the 'tipping point' for their innovative activities, their innovation performance will decrease. For firms which are more fit in with open innovation, their optimal external search breadth is wider and external search depth deeper. The regression results also show that for firms which are more fit in with open innovation, the impact of openness on innovation performance is more obvious. In general, high-technology industries are more suitable for open innovation. Industries in which technology is more intensive, the technology opportunity is richer and the synergy of open research and development is more significant, that is, the incoming spillovers of information are more obvious. But in high-technology industries, the risk of leakage, or outgoing spillovers are also apparent. Therefore, if a firm employs open innovation, it should analyze the characteristics of the industry it belongs to first, to determine its optimal degree of openness. "The more, the better" is not always true.

One limitation of this research is that the sample size of the survey is relatively small. In addition, firms responding to this survey are mostly located in Guangdong, Zhejiang, Shanghai, Fujian and other coastal cities. Therefore, we are unable to make any conclusion with regard to whether there are regional differences. Another limitation of this research is that it does not allow for the analysis of the importance of breadth and depth of external search to innovative performance within each individual knowledge channel. Future research should examine this issue by developing several fine-grained items for each of the knowledge sources.

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