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Technology Position and Profitability: The case of Chinese construction machinery firms*

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Abstract: This study examines the influence of technology accumulation on profitability of the firm. Technological differentiation is usually focused on for technology development, but learning is also an indispensable aspect in technology accumulation because firms try to absorb competitive differentiation developed by their competitors. We first verify that firms are learning against each other as well as differentiating their technologies using the patent applications of Chinese construction machinery firms. Next, we show that their profitability stabilizes as technological positioning becomes similar among firms through technology accumulation. Consequently, the technologies shared among firms in an industry can be a standard for their business, so that working as an entry barrier for entrants in the industry but also being a risk for the incumbents not to agilely adapt to a drastic technological shift.

***Keywords**:* technology position, similarity, differentiation, learning, China

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1. Introduction

How does technology accumulation influence profitability of the firm? Profitability is an indispensable indication for competitiveness of the firm and the possibility of business continuity under fierce competition, while firm performance can be evaluated by a variety of criteria based on accounting information. Besides, profitability can be influenced by a wide range of business factors such as innovation in business models and organizations, but technology is a key resource to increase the value of products and the productivity of firms.

Numerous studies already have been accumulated for the fundamental question of the relationship between technology development and profitability. As a result, it is known that research and development (R&D) intensity does not necessarily increase profit ratios (Lin et al., 2006). However, depending on some conditions, technological development can have a positive influence on profitability. The age of the firm is one condition, as it relates to more abundant experience and stronger external networks. Therefore, older firms have larger positive effects of R&D activities on performance than younger ones (Fortune and Shelton, 2014). On the other hand, younger Chinese mining firms have the negative influence of R&D activities on their profits due to the liability of newness (Rafiq et al., 2015). Therefore, accumulating experience that can be utilized later for businesses will matter for profitability.[1]

Previous related studies, however, seem to be lacking about what experience has an effect on profitability. To find it, this study focuses on the effect of technology accumulation on firm performance. Technologies accumulated under competition reflect the experience accumulation of each firm through technologically differentiating products and production processes against its competitors and simultaneously through socially learning its competitors’ technological advantages against each other.[2] In other words, firms are accumulating their technologies through their technology development

[1] The firm size will be also indirectly related to the age. Chinese large and medium-size manufacturers have the positive effects of R&D activities on profitability (Jefferson et al., 2006).

[2] If we divide learning into individual learning such as learning-by-doing inside the firm organization and social learning such as learning from others, then learning in this paper refers to the latter.

and through their competitors' technology development as well. While technological heterogenization by differentiation will improve profit margins, technological homogenization by learning will lower profit margins by neutralizing the technological advantage of each firm against each other. How does technological accumulation, which has such opposing effects on profit margins, ultimately affect profitability?

This study examines the relationship between technological accumulation through differentiation and learning and firm performance, based on the case of local Chinese construction machinery firms which are actively accumulating technologies in these years. First, we verify that while firms develop technologies that are technologically similar to their previous technologies as differentiation, they also develop technologies that are similar to their competitors' previous ones as learning, using the dataset of patent applications of Chinese firms.[3] Next, we examine the influence of technology accumulation on firm performance. It is shown that profitability stabilizes as the technological positioning in terms of technological fields becomes similar among firms through learning as well as differentiation.

The structure of this article is as follows. Section 2 introduces our method. Section 3 reports the results of our analysis. Finally, we summarize and conclude the analysis in Section 4.

2. Method

To compare the technological positioning of firms, this study calculates the cosine similarity between the technology positions of firms or between their patent applications.[4] Firm *X*'s or its patent application's technology position is represented as a vector, $\mathbf{F}^X = (F_1^X \dots F_n^X)$, composed by the proportions of patent applications in each technological field k, F_k^X. The similarity is a comparison of the direction of the vectors as follows:

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[3] Of course, because technological development is the development of new technologies, learning here means improvement based on existing technology or circumvention that realizes existing functions in a different way.

[4] The similarity between technology positions is defined in Jaffe (1986).

$$s^{XY} = similarity\,(\mathbf{F}^X, \mathbf{F}^Y) = \mathbf{F}^X\mathbf{F}^{Y\prime}/\sqrt{(\mathbf{F}^X\mathbf{F}^{Y\prime})(\mathbf{F}^X\mathbf{F}^{Y\prime})}.$$

The similarity between Firm X and Y or each firm’s patent applications indicates 1 if the vectors are in the same directions, and 0 if orthogonal. We use the concept of the similarity for our analysis in this study.

2.1 The Accumulation of Learning and Differentiation

First, we identify the fact that firms accumulate technologies through differentiation and learning. To do it, we examine which firm’s previous patent application is similar to each new patent application of each local firm. Specifically, we calculate the similarity $s_{ij,t}^{LA}$ between each technology position of Firm L’s patent applications i in year t, $\boldsymbol{F}_{i,t}^{L}$ and each technology position of all firms’ patent applications j up to the previous year t -1, $\boldsymbol{F}_{j,\le t-1}^{A}$:

$$s_{ijt}^{LA} = similarity(\boldsymbol{F}_{i,t}^{L}, \boldsymbol{F}_{j,\le t-1}^{A}). \quad (1)$$

Therefore, Equation (1) provides the similarity of each new patent application with each previous one.

Because the technology position here is a vector at the level of the patent application document, we use vectors generated by natural language processing (NLP) with the titles and abstracts of patent applications. At first, we remove noises and use nouns, verbs, and adverbs for preprocessing of natural language data. Next, we create 100-dimensional vectors with Doc2Vec for vectorization.

Based on the similarity between the NLP-based vectors of technology positions at the level of patent application document, we define Firm L’s own new technology here as follows. It is a Firm L’s new patent application that at least one Firm L’s previous patent application is in the three most similar patent applications among all firms’ previous ones. Therefore, with this definition, a new technology can be based on up to three firms’ previous technologies.

2.2 The Relationship between Similarity and Firm Performance

Next, we identify the effect of the technological similarity at the firm level on firm performance. To do it, we focus on the similarity between the technology position of a firm and that of the entire industry that the firm belongs to and examine the relationship between the similarity and firm performance. Specifically, we calculate the similarity s_t^{LA} between Firm L's cumulative technology position up to year t, $\boldsymbol{F}_{\leq t}^{L}$ and all firms' cumulative one up to the same year t, $\boldsymbol{F}_{\leq t}^{A}$:

$$s_t^{LA} = similarity(\boldsymbol{F}_{\leq t}^{L}, \boldsymbol{F}_{\leq t}^{A}). \quad (2)$$

Therefore, Equation (2) provides the similarity between the technology position of each firm and that of all firms in the same industry.

Because we can clearly understand technological fields that each firm is focusing on, the codes of International Patent Classification (IPC) of patent applications are used to create the vectors of technology positions. The IPC is a hierarchical classification of technological fields for patents. The IPC-based vectors are composed by the fractions of patent applications in each technological field classified by the IPC.

Based on the IPC-based vectors, we examine the relationship between the similarity at the firm level and profit rates such as the gross profit ratio, the operating profit ratio, and return on assets (ROA). Since profit has several definitions, we take up the three in this study. The details are complemented in the process of analysis of the next section.

2.3 The Case

In this study, we use the case of China's construction machinery industry. Because major firms have relatively similar product line-ups including excavators, wheel loaders, cranes, dump trucks, and so on, this industry is one of the industries where the competition among major firms in a code of industrial classification is comparatively clear.[5] There are a variety of construction machines with combinations of components for working at construction sites, and hydraulic systems for accurately moving the components.

To analyze the relationship between technology accumulation and firm performance, this study uses patent applications filed in China by local and foreign

[5] The construction machinery firms that we focus on are categorized in the North American Industry Classification System (NAICS) code 333120.

firms in the industry from 2001 to 2018, and accounting information of local Chinese firms in the industry.[6] The dataset is downloaded from Bureau van Dijk’s Orbis Intellectual Property on December 17, 2021.

Table 1.1 shows some major Chinese firms in the industry. Their main product line-ups are construction machinery but depending on each firm’s different history and merger and acquisition (M&A) strategies, they each have their own strengths among construction machines and manufacture a variety of products such as wind power generation equipment. The number of patent applications of each major firm has increased especially in the 2010s. The most common technological fields that all Chinese firms, including the major firms, have filed until 2018 are the working functions such as “E02F: Dredging; soil-shifting” (12.1%), “B66C: Cranes, etc.” (5.6%), and “E01C: Construction of roads, etc.” (5.1%) in the four-digit level of the IPC, and the hydraulic systems such as “F15B: Systems acting by means of fluids in general; Fluid-pressure actuators” (6.2%) in the same level.[7]

Table 1.1: Major Chinese Construction Machinery Firms, 2018

Name	Chinese Name	Sales (1,000 US$)	Gross Profit (1,000 US$)	Patent Applications* (Units)
Zoomlion Heavy Industry Science & Technology	中联重科	4,187,509.2	1,381,730.7	2,771
Sany Heavy Industry	三一重工	7,881,235.5	2,966,649.1	1,237
XCMG Construction Machinery	徐工机械	6,189,295.8	1,478,363.8	977
Liugong Changzhou Machinery	柳工	2,593,667.2	671,139.5	819

Note: * The cumulative number of patent applications as of 2018.

Source: Created by the authors based on Orbis Intellectual Property.

3. Analysis

3.1 The Accumulation of Differentiation and Learning

This subsection shows that the major Chinese firms have accumulated technologies

[6] We use only live patent applications at the time of download.

[7] The figures in parentheses indicate the percentage of the number in the relevant technological field to that of patent applications filed by Chinese construction machinery firms.

through differentiation and learning. Table 1.2 sorts out the results of Equation (1). The second and third columns in gray are the number of patent applications filed by each major Chinese firm and the percentage of its own technologies to all patent applications filed by each firm, respectively. According to the percentage of the total, approximately 20% to 50% of new patent applications are mainly based on their own previous technologies, although depending on firms. By definition, these new technologies of each firm possibly be similar to the previous technologies of its competitors as well, but at least they have a strong connection to its own previous ones.

Table 1.2: The Percentage of Own Technology by Firm, 2010–2018

(a) Sany

	Sany		Zoomlion	XCMG	Liugong	Chinese Firms Other Than Sany
	(Applications)	(%)	(%)	(%)	(%)	(%)
2010	126	38.1	6.3	2.4	5.6	57.1
2011	199	40.7	7.0	4.0	2.0	49.7
2012	479	37.0	40.1	5.4	5.6	76.4
2013	133	44.4	33.1	5.3	16.5	81.2
2014	49	46.9	40.8	8.2	8.2	81.6
2015	10	50.0	30.0	10.0	10.0	80.0
2016	7	28.6	57.1	0.0	14.3	85.7
2017	30	33.3	36.7	16.7	16.7	93.3
2018	11	0.0	18.2	9.1	9.1	81.8
Total	1,237	35.5	28.5	6.2	10.8	73.7

(b) Zoomlion

	Zoomlion		Sany	XCMG	Liugong	Chinese Firms Other Than Zoomlion
	(Applications)	(%)	(%)	(%)	(%)	(%)
2010	27	11.1	37.0	3.7	0.0	44.4
2011	413	9.7	40.7	2.2	4.6	53.8
2012	610	48.2	29.3	5.7	4.4	79.0
2013	756	57.8	38.0	7.3	5.8	85.2
2014	461	66.4	30.4	10.2	5.2	91.5
2015	180	73.3	30.0	10.6	5.0	93.9
2016	52	73.1	21.2	11.5	3.8	92.3
2017	47	51.1	14.9	14.9	8.5	91.5
2018	179	65.9	23.5	17.3	8.4	97.8
Total	2,771	51.2	31.8	8.2	6.0	82.0

(c) XCMG

	XCMG		Sany	Zoomlion	Liugong	Chinese Firms Other Than XCMG
	(Applications)	(%)	(%)	(%)	(%)	(%)
2010	11	0.0	36.4	9.1	0.0	45.5
2011	32	12.5	28.1	25.0	0.0	71.9
2012	68	13.2	36.8	44.1	1.5	83.8
2013	144	10.4	43.1	52.1	9.7	87.5
2014	174	11.5	33.3	58.6	2.3	90.8
2015	215	18.6	28.4	53.0	16.3	92.6
2016	132	31.8	23.5	48.5	12.9	93.9
2017	87	24.1	21.8	37.9	13.8	97.7
2018	98	17.3	15.3	33.7	29.6	94.9
Total	977	18.4	28.8	47.0	12.3	91.1

(d) Liugong

	Liugong		Sany	Zoomlion	XCMG	Chinese Firms Other Than Liugong
	(Applications)	(%)	(%)	(%)	(%)	(%)
2010	19	5.3	15.8	36.8	0.0	78.9
2011	38	10.5	15.8	0.0	5.3	52.6
2012	82	25.6	12.2	12.2	3.7	70.7
2013	84	23.8	34.5	36.9	2.4	83.3
2014	129	34.1	28.7	34.1	8.5	91.5
2015	65	30.8	29.2	41.5	9.2	95.4
2016	96	42.7	24.0	30.2	9.4	89.6
2017	119	34.5	20.2	37.8	18.5	93.3
2018	174	50.6	20.1	31.6	13.2	91.4
Total	819	36.5	23.0	30.4	9.4	87.8

Note: The number of "Total" is the sum of the values from 2001 to 2018.

Source: Created by the authors.

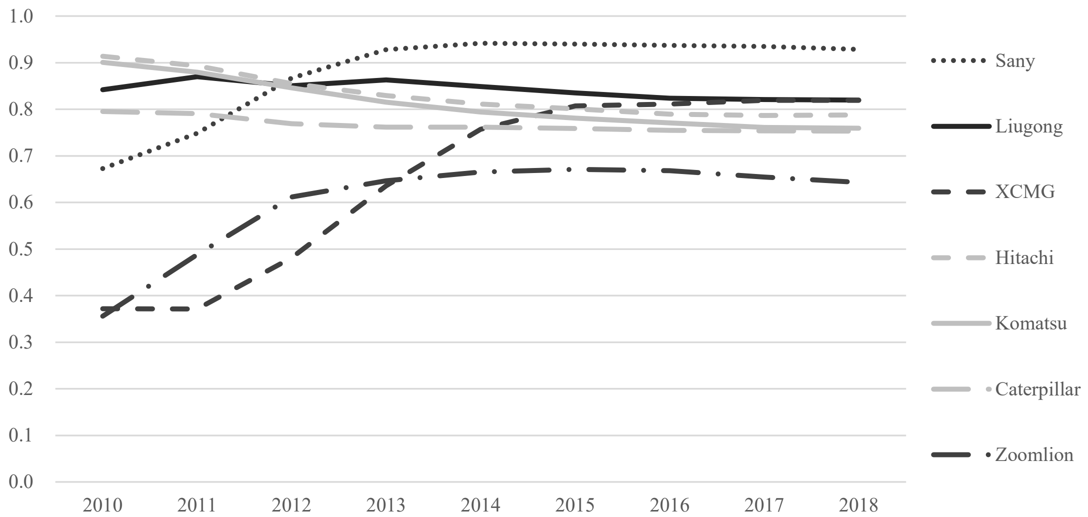
Next, the fourth to sixth columns show the percentage of the major firms other than its own firm. The shares in the total show that approximately 6% to 30% of the new patent applications has a strong connection to its competitors' previous ones, although possibly being similar to its own previous ones as well. As a result of social learning, each firm's technology will diffuse within the industry. Furthermore, based on the diffused technologies, each firm will continuously develop new differentiated technologies. Consequently, firms in that industry are unintentionally but collectively developing technologies for the business in the industry.

In addition, according to the far-right column, learning among Chinese firms is getting stronger, as the number of patent applications by Chinese firms increases. While foreign firms still have a large influence on the latest and core technologies, but in terms of numbers of patent applications, it shows that the competition for technological development among Chinese firms is also intensifying.

3.2 The Relationship between Similarity and Firm Performance

This subsection shows that the increasing similarity based on Equation (2) stabilizes profitability. At first, Figure 1.1 indicates the similarity of some major local and foreign firms in China with all patent applications in each year. The similarity of the foreign firms has not changed so much because they have already developed a lot of technologies and established their own technology positions, although they have a little decreased as the number of patent applications by Chinese firms has increased. On the other hand, the similarity of the Chinese firms has increased, as they have increased the number of patent applications and have been covering a variety of technological fields to operate construction machinery business like the major global firms do. Consequently, the technology positions of the firms in the figure have, to some extent, converged in terms of technological fields.

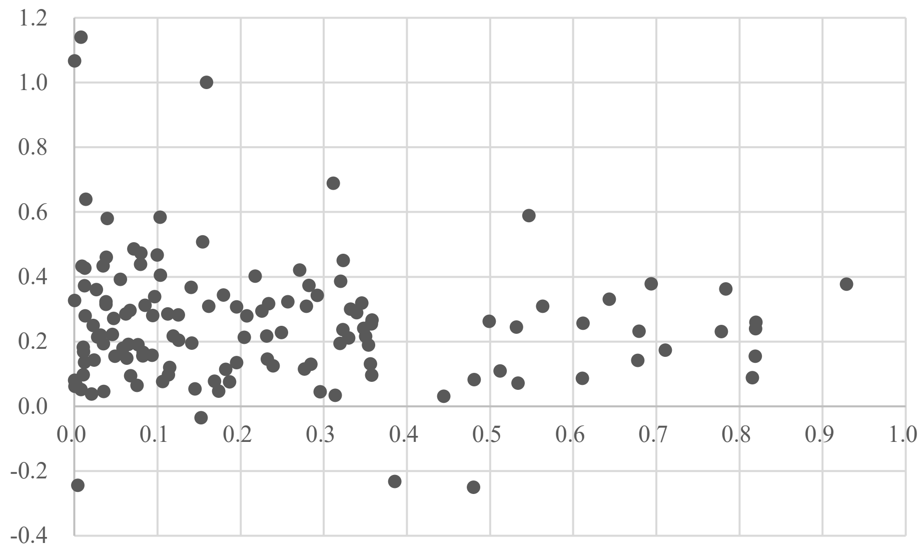
Figure 1.1: Similarity of Some Major Local and Foreign Firms in China, 2010–2018



Source: Created by the authors.

To overview the relationship, Figure 1.2 shows only the relationship between the similarity of Chinese firms and the ratio of gross profit to sales in 2018. Gross profit, which equals sales minus cost of sales, indicates the competitiveness of products themselves. In the figure, it is difficult to find a simple linear relationship between the two, but the variance of the profit rates at each similarity level seems to be decreasing. Of course, because there is a wide variety of firms including not only final-product firms like the major local and foreign firms shown above but also component suppliers and firms specialized in some specific business fields, therefore we cannot simply compare firms even within the industry. However, at least firms with higher similarity are similar in their product-lineups and their profit ratios are not as variation as the profit ratios of firms with lower similarity. Consequently, it can be assumed that within the construction machinery industry, the subdivision industry of firms with the relatively similar business has developed through technology accumulation under competition.

Figure 1.2: The Similarity and the Ratio of Profit to Sales, 2018



Source: Created by the authors.

Next, we estimate the relationship between the similarity and the variance of the profit ratios for the period between 2012 and 2018. The dependent variables are the variance of the gross profit ratio (*gp*), the operating profit ratio (*op*), and ROA (*roa*). Intervals to calculate the variance are created by dividing the similarity into a width of 0.1 each starting at 0. In addition, to increase the density of the intervals, they are placed in every 0.05 such as greater than or equal to 0 and less than 0.1, greater than or equal to

0.05 and less than 0.15, and greater than or equal to 0.1 and less than 0.2, so that they are overlapped. In each of these intervals, the average value of the similarity (s) as the independent variable is calculated to make the panel data.[8]

Table 1.3 shows the results of panel data regression.[9] The similarity has the negative relationship with the variance of the gross profit ratio and ROA, as we expected. The result of the operating profit ratio is not statistically significant due to the large variance in the middle of some intervals, although it also has a roughly negative relationship. Consequently, when technologies become similar, it is difficult for firms to obtain high profit margins, but by accumulating technologies, it is possible to stably run their businesses.

Table 1.3: Estimation Results

	gp	*op*	*roa*
s	-0.0289 (0.011)**	-0.168 (0.21)	-0.00670 (0.0031)**
Constant	0.0378 (0.0060)***	0.198 (0.11)*	0.00735 (0.0017)***
Sample size	118	118	118
Adj R^2	0.2961	0.0384	0.2223

Notes: Standard errors are in parentheses. ***, **, and * represent statistical significance at the 1, 5 and 10%, respectively.

Source: Created by the authors.

4. Conclusion

This study examined the influence of technology accumulation on profitability. We first verified that the major Chinese firms have been socially learning competitors' technologies as well as differentiating their technologies. Next, we showed that the profitability of Chinese firms stabilize as the technological similarity is increasing

[8] The equation to be estimated is as follows:

$$\text{variance}_{it} = \beta_0 + \beta_1 s_{it} + \varepsilon_{it}$$

where β_0 and β_1 are the parameters, ε is the error term, i indicates the interval, and t indicates the year.

[9] The results are obtained by the between estimation.

among firms. Firms face fierce competition from technologically similar competitors in the same industry, but in the process, they eventually accumulate technologies that are different from those of firms outside the competition.

Consequently, the technologies shared among firms in an industry can be a standard or necessary condition for their business in the industry. To be specific, firms in the industry need to have the shared technologies in order to enter the industry and newly add differentiation on existing basic and popular products in that industry, unless they can depend on outside firms such as suppliers or specialized firms with the shared technologies.[10] Therefore, the standard can work as a sunk cost or an entry barrier for new entrants in the industry, if there is a significant technological gap between incumbents and entrants. On the other hand, it may be a risk for the incumbents not to agilely and flexibly adapt to a drastic technological shift due to the inertia effect of the existing standard. In other words, if the standard drastically changes, such laggard firms will have bad performance, and in some cases, the entire industry may be disrupted.

In particular, the Forth Industrial Revolution is currently changing the functions and structures of many products and services. Applying Internet of Things (IoT) to construction machinery is also rapidly progressing. To understand the relationship between technology accumulation and performance more, further research is needed on the difference in the stage of industrial development and the impact of technological shifts.

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