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Koichiro KIMURA,* Hiroshi MATSUI, Kazuyuki MOTOHASHI, Shun KAIDA, and Janthorn SINTHUPUNDAJA

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Keywords: technology position, similarity, patent, China
JEL classification: O3, L1, L6

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* Corresponding author: Associate Senior Research Fellow, Institute of Developing Economies (Koichiro_Kimura@ide.go.jp)

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INSTITUTE OF DEVELOPING ECONOMIES (IDE), JETRO
3-2-2, WAKABA, MIHAMA-KU, CHIBA-SHI
CHIBA 261-8545, JAPAN

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Koichiro KIMURA,[†] Hiroshi MATSUI,[‡] Kazuyuki MOTOHASHI,[§]
Shun KAIDA,[**] and Janthorn SINTHUPUNDAJA[††]

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[†] Associate Senior Research Fellow, Institute of Developing Economies, Japan

[‡] Senior Manager, Deloitte Tohmatsu Consulting, Japan

[§] Professor, The University of Tokyo

[**] Manager, ABeam Consulting Indonesia

[††] Consultant, ABeam Consulting Thailand

1. Introduction

How do firms change their technological positioning under fierce competition? A firm's technological competitiveness is determined relative to its competitors' technologies. Therefore, firms need to constantly change their relative technology positions through technology accumulation in two different directions. One direction is to develop new technologies that achieve innovations, product differentiation, or business portfolio differentiation. Another direction is to learn competitors' technologies that achieved differentiation.[1] In other words, firms are increasing the technological distance between their and competitors' technology positions through differentiation and simultaneously decreasing the distance between them through learning. Consequently, competition has a significant impact on the type of technology that a firm accumulates between the contrasting two choices.

Many studies on technological similarity have been accumulated. Jaffe (1986) introduced a way to measure the similarity between industries and demonstrated that this similarity has a positive effect on these industries' technology spillovers. Since then, studies showing spillovers have been accumulated under various economic conditions. Bloom et al. (2007) showed both positive spillover and negative business stealing effects through such similarity but that the former is dominant overall. Moreover, Forman and van Zeebroeck (2019) verified that this similarity increases the citation likelihood among R&D centers within a firm after Internet adoption. Measuring this similarity has contributed to our understanding of the economy.

However, related studies have often calculated this similarity based on a single aspect: the similarity between the technology positions of industries or firms at a certain point in time. Therefore, this similarity has not been explicitly shown in the two directions of whether technological development at a point in time is relatively similar to competitors' previous technologies for learning or not similar to them for differentiation.

In this study, we develop a method for decomposing the change in technology position into differentiation and learning. Specifically, using the case of Chinese industrial robotics firms that have been rapidly increasing their number of patent

[1] In addition to learning, technology diffusion and imitation are also included in the same direction.

applications, we show how their technology positions are changing relative to a Japanese first-mover firm in the same industry. Moreover, this study shows that after these robotic firms have approached a Japanese first-mover firm's technology position, they also begin to accumulate technologies through technological differentiation. In other words, the accumulation of basic technologies for the robotics business can become a foundation or precondition for the accumulation of proprietary technologies. We expect to contribute to the discussion on the pattern of industrial development and changes in the industrial structure from the viewpoint of the pattern of technology accumulation at the firm level.

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

2. Method

2.1 The similarity

In this paper, we show a pattern of firms' technology accumulation by calculating the similarity between technology positions. Basically, the similarity between two firms' technology positions is defined based on Jaffe (1986) as follows. If the fractions of Firm A's and B's patent applications in each technology field k are F_k^A and F_k^B, respectively, the vectors of Firm A's and B's technology positions are $\mathbf{F}^A$ and $\mathbf{F}^B$, respectively. Then, the cosign similarity s^A between Firm A and B is as follows:

$$s^A = similarity(\mathbf{F}^A, \mathbf{F}^B) = \frac{\sum_{k=1}^{m} F_k^A F_k^B}{\sqrt{\sum_{k=1}^{m} (F_k^A)^2}\sqrt{\sum_{k=1}^{m} (F_k^B)^2}}.$$

The s^A notation denotes that it is based on Firm B as the standard of comparison. The similarity indicates 1 if the vectors are in the same directions and 0 if they are orthogonal.[2] The vector elements can be composed of technological field codes from the International Patent Classification (IPC) assigned to each patent application, the

[2] If a vector has a negative element(s), the similarity can also be negative.

results of natural language processing (NLP) of the titles and the abstracts of patent applications, and so on.

(1) Similarity 1: Similarity between IPC-based technology positions by year

First, we show whether the Chinese firms' technology positions are moving closer to the Japanese firm's position. Specifically, we compare each Chinese firm's IPC-based technology positions—created using their individual patent applications filed up to each year *t*, $\mathbf{F}^{A}_{\leq t}$—with the Japanese firm's patent applications, $\mathbf{F}^{B}_{\leq t}$:

$$s^{A}_{t} = similarity(\mathbf{F}^{A}_{\leq t}, \mathbf{F}^{B}_{\leq t}).$$

In other words, this similarity represents the similarity between the cumulative technology positions of the two firms for each year.

Therefore, although technology positions can vary by scope within all of a firm's activities, this study as a first approach covers an entire firm to observe the overall pattern of technology accumulation by new entrants. Because a firm's technological competitiveness also reflects technologies mainly used in related businesses or products, such as the synergy effect, having the overall view of a firm as a first approach is important. In this regard, we carefully interpret and discuss the meaning of each similarity to avoid misleading the scopes of differentiation and learning.

To create vectors, we use the Bureau van Dijk (BvD) Orbis Intellectual Property (Orbis IP) database. BvD is a provider of firm information worldwide, and Orbis IP contains accounting information and intellectual property information on firms. We downloaded the patent applications filed by firms at the patent offices in their home countries—China or Japan—in August and September 2020.

(2) Similarity 2: Similarity between IPC-based new and previous technology positions by year

Next, we show whether the new patent applications of the Chinese firms in each year are relatively moving closer to their or the Japanese firm's previous technologies. Specifically, we compare each Chinese firm's IPC-based new technology position created using patent applications filed in each year, $\mathbf{F}^{A}_{t}$, with its own previous technology position, $\mathbf{F}^{A}_{\leq t-1}$, and with the Japanese firm's previous one, $\mathbf{F}^{B}_{\leq t-1}$, respectively:

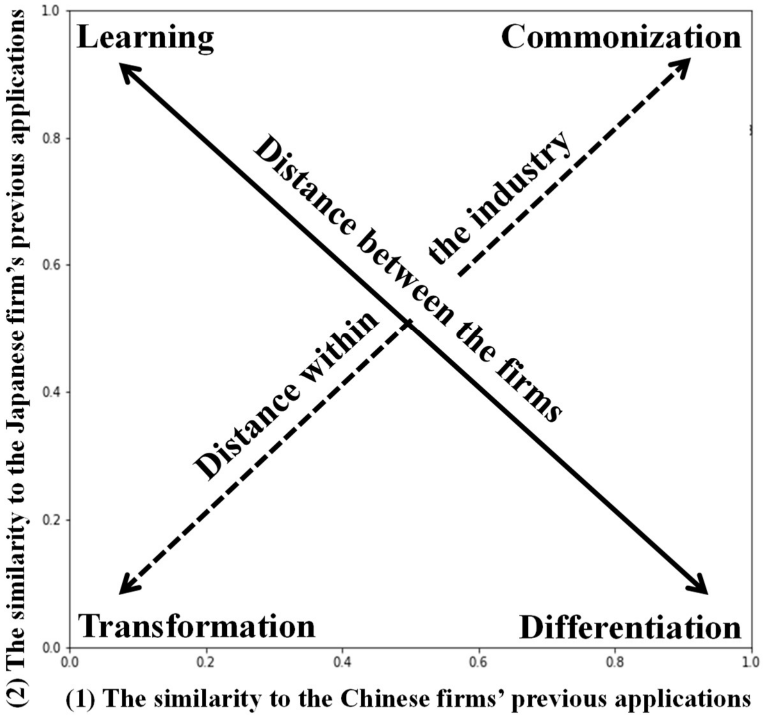
$$s_t^{AA} = similarity(\mathbf{F}_t^A, \mathbf{F}_{\leq t-1}^A) \text{ and}$$

$$s_t^{AB} = similarity(\mathbf{F}_t^A, \mathbf{F}_{\leq t-1}^B).$$

In other words, by comparing the two similarities, we can find the relative direction in which the Chinese firm's new technology is heading between its own and the Japanese firm's previous technologies.

Figure 1 illustrates the relationship among the locations of the two similarities. The horizontal axis shows the similarity with the Chinese firms' previous technologies, and the vertical axis shows the similarity with the Japanese firm's previous technologies. If $s_t^{AA} > s_t^{AB}$, that is, a coordinate is located below the right-upper 45-degree line that overlaps the dashed double-headed arrow, then the new technologies have a relatively strong tendency toward differentiation from the Japanese firm's previous technologies. In contrast, if $s_t^{AB} > s_t^{AA}$, that is, a coordinate is located above the right-upper 45-degree line, then the new technologies have a relatively strong tendency toward learning from the Japanese firm. Therefore, the tendency of differentiation and learning becomes stronger along the solid arrow, which represents the technological distance between the two firms as they approach the lower right and upper left areas, respectively.

Figure 1: The Relative Technology Position between Two Firms



Source: Created by the authors.

Here, we should be clearer about the meaning of differentiation and learning in this study. Differentiation that comes from between existing firms with enough of the basic technology and know-how in their industry can lead to the launch of a new product or service that has never been previously supplied in the industry. In contrast, differentiation that comes from between an existing and a new firm might just reflect a technological gap or backwardness between the old and young firms. Alternatively, such differentiation might inversely reflect a technological shift or change that disrupts an existing industry and leads to industrial structure changes through a generational shift between them. Hence, the evaluation of each differentiation needs to consider the characteristics of the competitive environment among firms.

Next, learning in this study refers to overlapping technological fields among firms. Of course, every patent application necessarily claims some novelty in the country in which the application is filed; therefore, the result of only learning something never leads to a patent application. Because we are interested in the technological fields that each firm focuses on, we evaluate differentiation and learning through the changes in their technology positions.[3]

At the end of this subsection, we explain the movement along with the dashed double-headed arrow. The arrow represents the change in technological distance compared with each firm's previous technologies within the industry. If both s_t^{AA} and s_t^{AB} become close to 1, that is, a coordinate is located toward the upper right area of the dashed arrow, then the new technologies are commonalized among the firms in an industry. In other words, this change represents a specialization at the whole industry level and the emergence of a new industry from an existing industrial structure.

In contrast, if both s_t^{AA} and s_t^{AB} become close to 0—a coordinate is located toward the lower left area of the dashed arrow—then, the new technologies become transformational among the firms in an industry. In other words, this change represents technological restructuring at the whole industry level. Factors that influence technology positions can come not only from competitors within the same industry but also from outside the industry. Our method can capture the existence of an impact from outside and inside an industry, although it cannot identify the firm outside the industry that is having an impact.

(3) Similarity 3: Similarity between NLP-based new and previous patent applications by document

Finally, we show whether each new patent application of the Chinese firms is much closer to their previous technology or to the Japanese firm's previous technology at the document level. The IPC-based vectors can indicate the technology position at the firm level but not the document level. Therefore, we compare the similarity of the technology positions from patent applications using vectors generated by NLP with the words in the titles and the abstracts of patent application documents as the natural language data.

Specifically, we conduct the following steps for data cleaning and preprocessing of the natural language data. First, we delete signs such as "%" and "?" and lowercase all of the alphabetical characters. In addition, we delete the headings in the abstracts of the patent applications filed in Japan, that is, "Problem to be solved" and "Solution," because they do not directly indicate the technological field itself. Second,

[3] We also do not consider whether the patent application has been granted, whether it is internationally novel, or whether the patent quality is high.

we use only nouns, verbs, and adverbs and convert them into stems with a natural language toolkit. Then, we make each preprocessed document a 100-dimensional vector with Doc2Vec.

Subsequently, we compare the Chinese firm's NPL-based new technology positions, $\mathbf{F}_{i,t}^{A}$, with its own previous technology positions, $\mathbf{F}_{j,\leq t-1}^{A}$, and with the Japanese firm's previous positions, $\mathbf{F}_{j,\leq t-1}^{B}$, respectively:

$$s_{ij,t}^{AA} = similarity(\mathbf{F}_{i,t}^{A}, \mathbf{F}_{j,\leq t-1}^{A}) \text{ and}$$

$$s_{ij,t}^{AB} = similarity(\mathbf{F}_{i,t}^{A}, \mathbf{F}_{j,\leq t-1}^{B}).$$

In other words, we can find out, which of each new patent application of the Chinese firms is similar to each of all previous patent applications of both the Chinese and Japanese firms.

Here, if the three most similar previous applications to each new application include at least one of the Chinese firm's previous applications, we consider the new application as the Chinese firm's own technology. Considering the NLP results so rigorously as to say that previous applications below the second most similarity represent technology in a completely different lineage from their own technology is difficult. Therefore, we here assume that the technology is in its own differentiation if included in the top three.

2.2 The case

We use Chinese robotics firms as the case study to identify how firms in an emerging economy accumulate technologies when attempting to establish a new robotics business for them. In China, labor costs began to soar in the mid-2000s, and demand for industrial robots began to rise. These changes led to the rapid development of the Chinese robotics industry. We attempt to determine to what extent they are technologically catching up with the first-mover firm and to what extent they are simultaneously differentiating from this firm.

Table 1: Major Chinese and Japanese Industrial Robotics Firms, 2010–2018

		2010	2011	2012	2013	2014	2015	2016	2017	2018
Yaskawa										
Sales	(mil. $)	35,709	37,384	32,967	35,350	33,316	36,514	35,242	41,793	42,803
R&D/Sales	(%)	3.3	3.4	3.5	3.9	3.8	4.1	4.6	4.3	4.4
Patent Applications	(patents)	480	546	442	515	266	234	98	128	77
Fanuc										
Sales	(mil. $)	53,675	65,550	52,936	43,848	60,758	55,351	47,920	68,424	57,300
R&D/Sales	(%)	3.5	3.8	4.0	4.1	3.9	5.5	7.9	7.3	8.8
Patent Applications	(patents)	172	287	449	556	866	1,000	1,118	1,417	1,006
Siasun										
Sales	(mil. $)	814	1,218	1,627	2,130	2,459	2,566	2,900	3,719	4,463
R&D/Sales	(%)	0.9	4.4	3.6	2.9	4.5	3.7	3.5	4.6	4.8
Patent Applications	(patents)	17	7	108	101	47	113	127	210	235
Step										
Sales	(mil. $)	756	1,040	1,330	1,632	2,123	2,307	3,900	5,201	5,102
R&D/Sales	(%)	0.0	7.1	7.2	6.8	7.7	9.3	5.4	4.8	5.1
Patent Applications	(patents)	8	9	9	9	32	39	59	30	23
Estun										
Sales	(mil. $)	n.a.	n.a.	n.a.	n.a.	830	739	967	1,635	2,109
R&D/Sales	(%)	n.a.	n.a.	n.a.	n.a.	10.6	11.1	8.4	7.6	7.8
Patent Applications	(patents)	4	9	10	13	11	4	14	10	3
Effort										
Sales	(mil. $)	n.a.	n.a.	271	355	366	353	720	1,193	1,908
R&D/Sales	(%)	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Patent Applications	(patents)	5	0	2	3	14	11	11	12	19

Note: The values for Yaskawa and Fanuc are based on the fiscal year in Japan (April to March).

Source: Created by the authors based on Orbis IP.

Specifically, we focus on the following four major indigenous Chinese firms that have an industrial robotics business as a major business line and have produced more than 2,000 units per year as of 2018 as shown in Table 1 (Fuji Keizai, 2019). Siasun Robot & Automation (Siasun), founded in 2000, is a robotics subsidiary of the Chinese Academy of Sciences. Step Electric (Step), founded in 1995, and Estun Automation (Estun), founded in 1993, are both developing industrial robots using control technology that they accumulated. Efort Intelligent Equipment (Efort), founded in 2007, is a robot manufacturer with an investment from Chery, a major Chinese automotive manufacturer.

These firms are compared with Yaskawa Electric (Yaskawa) as a first-mover firm in the industry. Yaskawa, founded in 1915 as a motor manufacturer, started its industrial robotics business in the 1970s. However, such choice of the standard firm for comparison never means that we expect new entrants' technology positions to become the same as that of a first-mover firm in the same industry. Although we chose the first-mover firm to focus just on new entrants' catch-up process, as mentioned in the previous subsection, our method expects the possibility of capturing a new entrant with new technology or technological change as differentiation or transformation, respectively. Therefore, choosing a standard firm appropriately according to the purpose of the analysis is necessary.

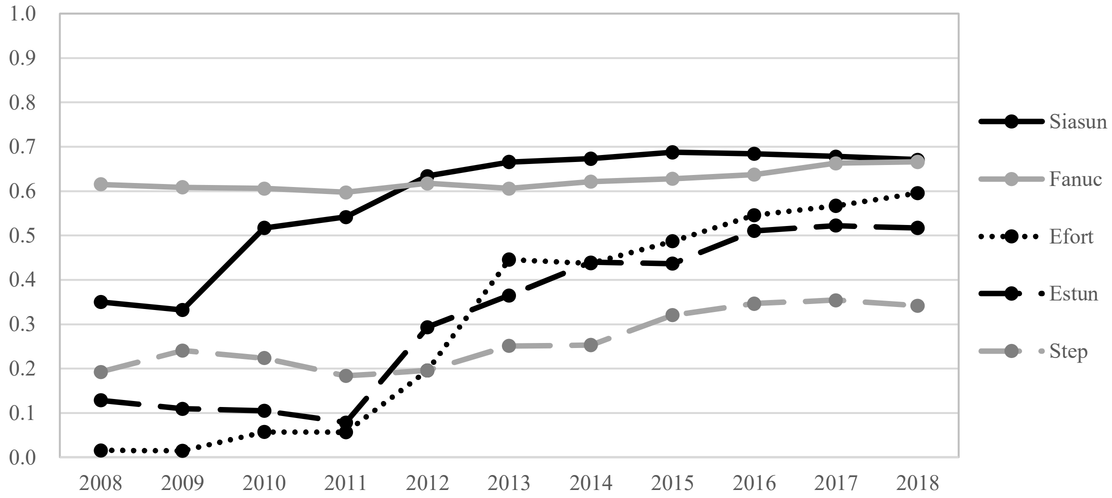
In addition, we also compare Yaskawa with another first-mover firm, Fanuc, to highlight the differences between the new entrants and the first-mover firm. Fanuc, founded in 1956 as a division of Fujitsu for numerical control and servo systems, began developing robots in the 1970s and spun off as a subsidiary in 1972.

3. Analysis

3.1 Similarity 1: Similarity between Cumulative Patent Applications at the Firm Level

First, we show the result of "(1) Similarity 1: Similarity between IPC-based technology positions by year" in the previous section. Figure 2 illustrates that the technology position of every Chinese firm has generally become closer to that of Yaskawa as the number of patent applications increased. Moreover, the trend is more pronounced when the number of patent applications is stronger; therefore, Siasun in particular increased from approximately 0.3 to approximately 0.7. The increasing similarities of the Chinese firms indicate that the industry specializing in robot production in China has technologically differentiated itself from the existing industrial structure.

Figure 2: The Similarities between the Cumulative Applications, 2008–2018



Source: Created by the authors.

However, the similarities increased and then almost leveled off. Although the number of patent applications of the Chinese firms has not decreased, the change in similarity has become smaller, possibly indicating that their technology positions have no longer significantly changed. This smaller change in similarity is a characteristic of Fanuc in particular. Because Fanuc has already filed many patent applications, partially similar to Yaskawa, and has established its technology position, the similarity is almost unchanged throughout the period. Consequently, the Chinese firms are also expected to change little in similarity as they further establish their technology positions.

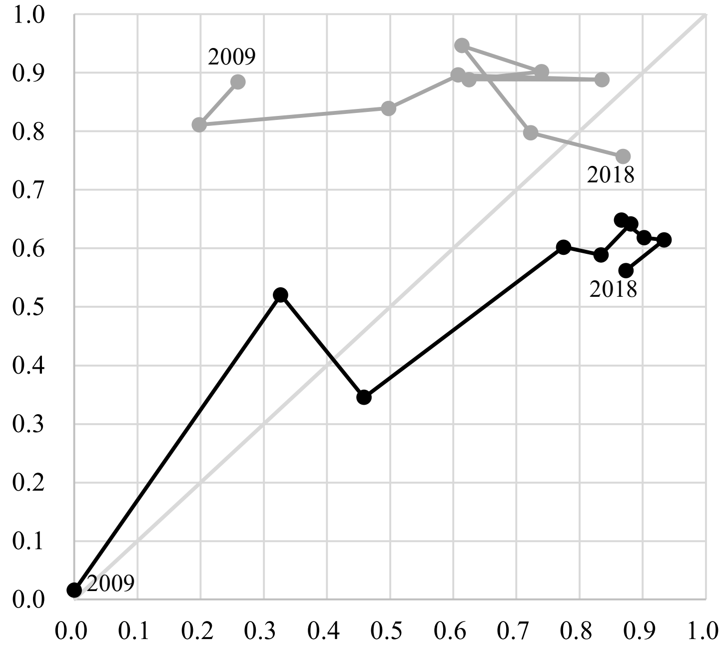
Therefore, we focus on the change in each Chinese firm's technology position in the next subsection. Specifically, the extent to which Chinese firms' new technologies in each year are similar to Yaskawa's previous technologies is examined.

3.2 Similarity 2: Similarity between New and Previous Patent Applications at the Firm Level

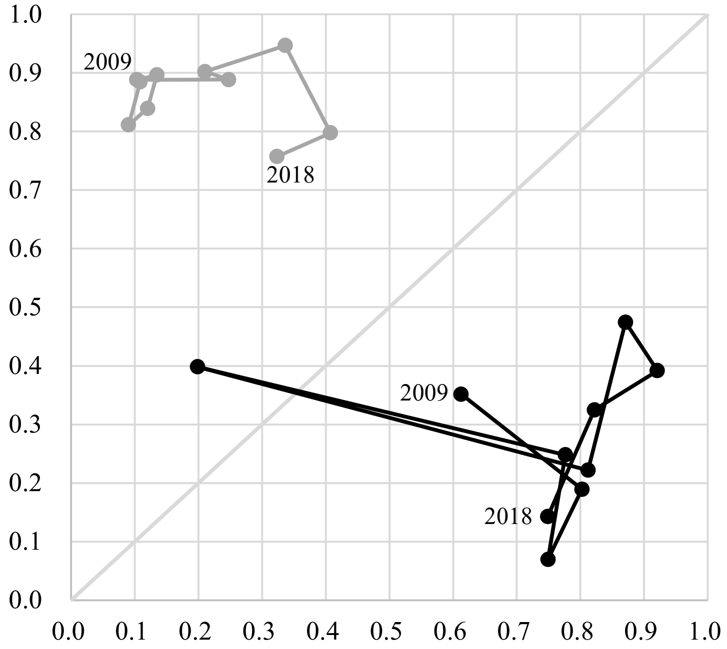
Next, we show the result of "(2) Similarity 2: Similarity between IPC-based new and previous technology positions by year." The black/gray lines in Figure 3 illustrate the comparison of the new patent applications of each Chinese firm/Yaskawa with the previous patent applications of Yaskawa/each Chinese firm using the coordinate plane of Figure 1. However, because the horizontal and vertical axes represent the similarities with the Chinese firms' and Yaskawa's previous patent applications, respectively, and not similarities with those of their firms' and their competitors', note that the directions of differentiation and learning on the solid arrow for Yaskawa are reversed from that for the Chinese firms shown in Figure 1. In addition, the figure for Fanuc is also included as a comparison with the Chinese firms.

Figure 3: The Similarities between New and Previous Applications, 2009–2018

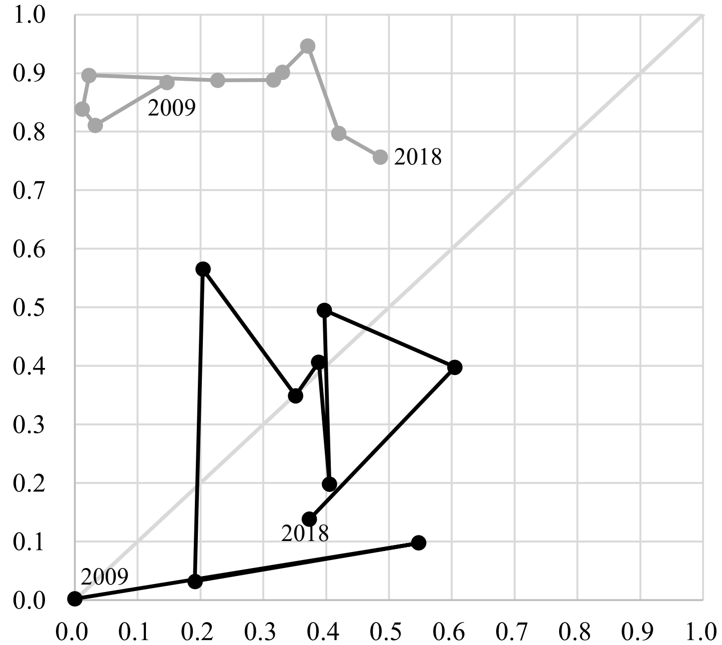
(a) Siasun vs. Yaskawa



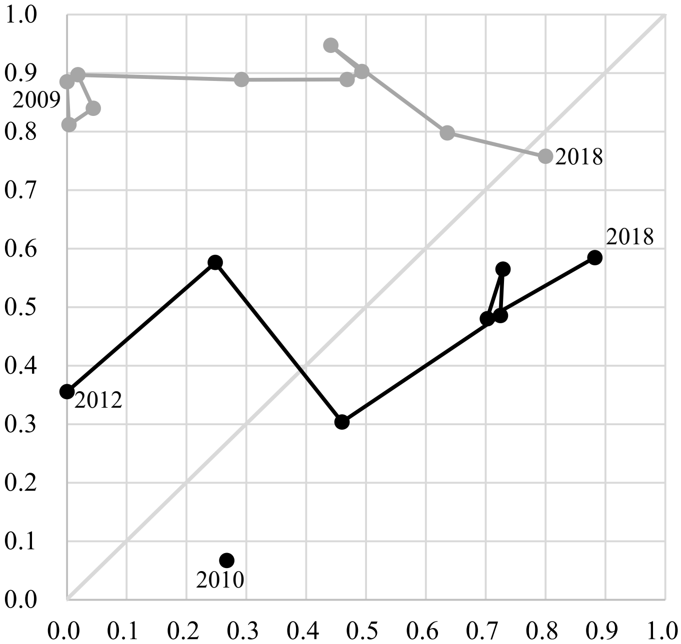
(b) Step vs. Yaskawa



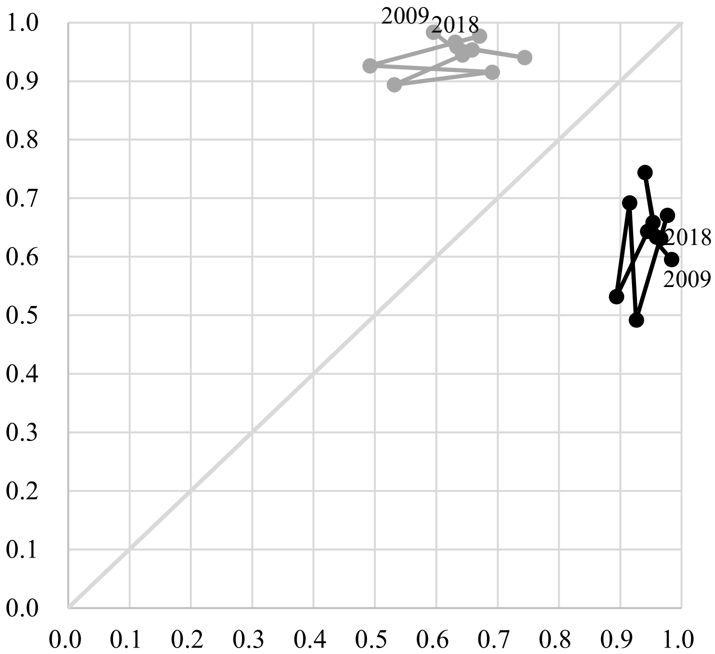
(c) Estun vs. Yaskawa



(d) Efort vs. Yaskawa



(e) Fanuc vs. Yaskawa



Source: Created by the authors.

The black lines of the Chinese firms tend to move to the upper right overall, although Step is often closer to its own previous technology positions. In other words, the Chinese firms' technologies have become more commonized with those of Yaskawa. The commonization is also expressed through the fact that Yaskawa's gray lines moved almost parallel to the right along the horizontal axis. The Chinese firms have accumulated technologies in many of the same technological fields as Yaskawa's and, thus, share technological fields for the industrial robotics business.

In addition to the commonization, Figure 3 illustrates that the Chinese firms' new technologies tend to be relatively close to their previous patent applications than Yaskawa's patent applications. This situation has been particularly pronounced since approximately 2014, when the number of patent applications filed each year began to increase. Therefore, as technological development intensifies, firms' unique technology positions are also being formed.

Actually, even for Siasun in which the similarity to Yaskawa increased steadily, the movement of the similarity is not monotonous. Table 2 shows whether Siasun's new technologies are moving toward relative commonization (C) or transformation (T) and whether they are moving toward learning (L) or differentiation (D) through a comparison of the similarity in each year to that in the previous year. For "Commonization (C)/Transformation (T)," if both differences from the previous year are positive/negative, then the direction is considered C/T. Moreover, for "Learning (L)/Differentiation (D)," if the difference in the difference is negative/positive, then the direction is considered L/D. As the table shows, learning is relatively dominant in some years, whereas differentiation is dominant in other years.

Table 2: The Similarity and Its Directions: Siasun

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Similarity										
s_t^{AA}	0.00	0.33	0.46	0.77	0.83	0.88	0.87	0.90	0.93	0.87
s_t^{AB}	0.02	0.52	0.35	0.60	0.59	0.64	0.65	0.62	0.61	0.56
Commonization (C) / Transformation (T)										
$s_t^{AA} - s_{\leq t-1}^{AA}$	–	0.33	0.13	0.32	0.06	0.05	-0.01	0.04	0.03	-0.06
$s_t^{AB} - s_{\leq t-1}^{AB}$	–	0.50	-0.18	0.26	-0.01	0.05	0.01	-0.03	0.00	-0.05
C or T	–	C		C		C				T
Learning (L) / Differentiation (D)										
$\left(s_t^{AA} - s_{\leq t-1}^{AA}\right) - \left(s_t^{AB} - s_{\leq t-1}^{AB}\right)$	–	-0.18	0.31	0.06	0.07	-0.01	-0.02	0.07	0.04	-0.01
L or D	–	L	D	D	D	L	L	D	D	L

Source: Created by the authors.

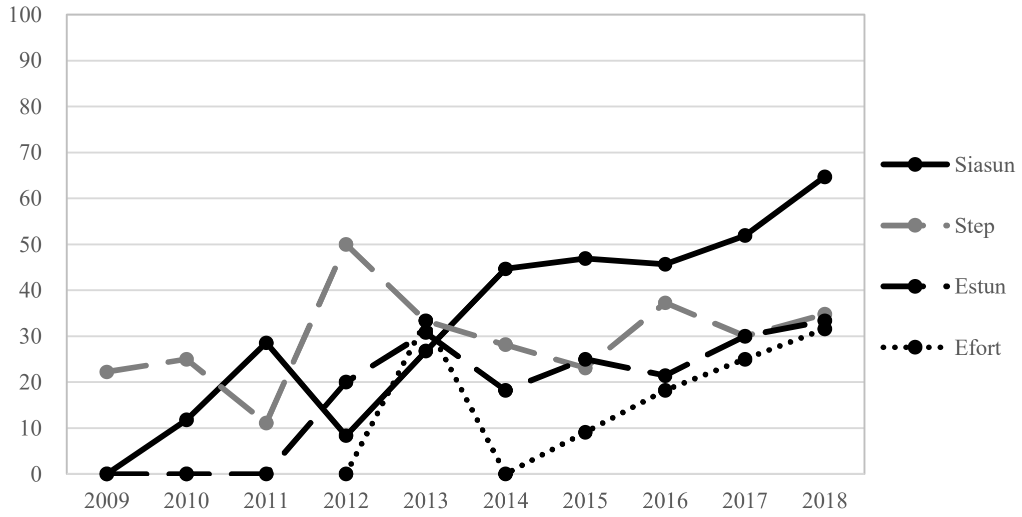
Such differences in the technological fields exist because each firm differentiates its product lineup and simultaneously conducts different businesses based on its growth process. Among robotics-related technologies, Siasun has been forming strength by focusing on medical and transportation applications, whereas Efort is also focusing on painting applications. Among the machine design and control technologies, Step and Estun also have been developing a controller system for elevators and metal processing machinery, respectively. When also accumulating various technologies, each firm is aiming to expand production and improve the quality of robots.

3.3 Similarity 3: Similarity between New and Previous Patent Applications at the Document Level

Next, we show the result of "(3) Similarity 3: Similarity between NLP-based new and previous patent applications by document." In the previous subsection, we showed that each firm has been accumulating its technologies and approaching Yaskawa's previous technology positions. However, whether the number of their own technologies is also increasing even at the document level is unclear; therefore, we show this trend in this subsection.

Figure 4 illustrates the percentage of patent applications that include each firm's own previous document in the top three similar documents. Because the number of patent applications filed by each firm is still small up to approximately 2013 and the percentage of each firm widely fluctuates, we cannot find a clear trend in the period. In contrast, the number of patent applications began to increase in approximately 2014, and the percentages simultaneously display an upward trend.

Figure 4: The Percentage of Applications Similar to Own Previous Applications, 2009–2018 (%)



Source: Created by the authors.

Consequently, although the Chinese firms are technologically approaching Yaskawa while accumulating technologies common to the robotics business, but simultaneously each firm begins to accumulate its unique technologies. Of course, because they have accumulated robotics-related technologies, the increasing percentages never mean that the Chinese firms are developing technologies that are completely different from those of Yaskawa. In contrast, also true is that technologies linked only to Yaskawa's technological lineage are decreasing. Therefore, we can say that the Chinese firms are also beginning to develop technologies linked to their own technology lineage, and the technologies can become a source of further innovation in the future.[4]

[4] This is consistent with the fact that Siasun is diversifying its technologies along with its technological accumulation relative to its competitors' technological positions (Kimura et al., 2021).

4. Conclusion

In this study, we first showed a pattern of firms' technology accumulation. Although the Chinese firms have become close to the Japanese first-mover firm's technology position, they also have begun to accumulate their own technologies. The accumulation of basic technologies for the business can be a foundation or precondition for the accumulation of proprietary technologies.

Consequently, to comprehend the characteristics of firms' technological development, we need a perspective that technologies are a relative combination of similarities and differences in comparison with competitors. In fact, the industry is the set of firms that are technologically more similar than firms in other industries but also are different from other firms in the same industry. Therefore, we should focus on the relationship between both of them and not only either the similarities through learning or the differences through differentiation and innovation.

Therefore, second, we showed a method to analyze both sides of the similarities and differences using the firm's technology position as its technological structure and its similarity. In this study, we analyzed the growth of firms and the development of the new Chinese industry. In addition, we can also analyze the relationship between industrial structure changes and economic growth by focusing on the technological similarities and differences among firms within different industries.

Of course, the similarities and differences among firms within an industry have been extensively discussed in economics; however, they have been often focused on separately. When analyzing markets at the micro level, we often discuss the impact of product differentiation on markets without specifically indicating the similarities among the firms in an industry. Therefore, we can say that the existence of similarities is not ignored but also not explicitly shown. Moreover, when analyzing industrial structures at the macro level, we often discuss the impact of changes in industrial structure and product variety on economic growth without specifically indicating the differences among firms in an industry (Aghion and Howitt, 2009; Herrendorf et al., 2014). In other words, an industry is expressed just by a representative firm and not by a set of firms with differences as well as similarities. Hence, in this study, we analyzed the industry of the medium level especially focusing on the opposing aspects of similarities and differences among firms within an industry.

Further, we need to accumulate more case studies to find new patterns of technology accumulation and develop a method to analyze the mechanism of the patterns. Given the rapid technological and industrial structure changes brought about by the current Fourth Industrial Revolution, comparing the technologies of a firm with firms in both the same and different industries is important.

References

Aghion, Philippe, and Peter W. Howitt (2009) *The Economics of Growth*, Cambridge: The MIT Press.

Bloom, Nicholas, Mark Schankerman, and John van Reenen (2013) "Identifying Technology Spillovers and Product Market Rivalry," *Econometrica* 81(4): pp. 1347–1393.

Forman, Chris and Nicolas van Zeebroeck (2019) "Digital Technology Adoption and Knowledge Flows within Firms: Can the Internet overcome geographic and technological distance?" *Research Policy* 48(8).

Fuji Keizai (2019) *Survey on the Latest Trends of Fast-growing Chinese Emerging Robot-related Players* [*Kyu Seicho suru Chugoku Shinko Robotto Kanren Pureya no Saishin Doko Chosa*], Tokyo: Fuji Keizai (in Japanese).

Herrendorf, Berthold, Richard Rogerson, and Ákos Valentinyi (2014) "Growth and Structural Transformation," in Philippe Aghion and Steven N. Durlauf eds. *Handbook of Economic Growth*, Volume 2, Burlington: Elsevier Science.

Jaffe, Adam (1986) "Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value," *The American Economic Review* 76(5): pp. 984–1001.

Kimura, Koichiro, Hiroshi Matsui, Kazuyuki Motohashi, Shun Kaida, and Janthorn Sinthupundaja (2021) "Technology Development and Similarities," in Koichiro Kimura (ed.) *Impacts of Innovation on Firm Performance and Industrial Development in East Asia*, Bangkok: IDE-JETRO Bangkok.