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Tracing the Convergence of Industrial Sectors: Has the 4th Revolution Arrived Already? Or Are We on the Track?

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〈Abstract〉

While an increasing number of people across diverse audience groups are engaging in discussions about the onset of the 4th industrial revolution, it remains challenging to pinpoint the symptoms of this phenomenon. This research, recognizing this difficulty, employed a time-series data-tuned cluster analysis to uncover evidence of industrial and technological convergence among the United States, Japan, and Korea by using time-series industrial R&D data and industrial wage data as indirect measures of industrial competitiveness and technology convergence. The results showed that the recent U.S. case of 2010-2019 data clearly featured the" phenomenon Tesla", which shows the convergence of Aerospace, Transportation equipment, and software. Supporting evidence for that comes from the results from the previous periods in the three countries, which shows a high concentration of cor manufacturing sectors, but no symptoms of convergence.

Keywords : Convergence, Industrial Sector, 4th Revolution

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1. Introduction

As many people in different audience would agree, we are marching toward the deepening stages of the 4th revolution[1]. One of the major symptoms of the 4th revolution has been discussed as the convergence of technologies and industrial sectors[2]. This paper aims at finding and tracking, if there are any, evidence for the phenomenon. Utilizing numerical taxanomy of times series data of the U.S., Japan, and Korea since 1960s on, this research tried to track whether there has been gradual movement toward the convergence. Due to differences in data collection in the three countries, rather than having the exactly identical time frame , this article tried to compare three different countries at slightly different period. Despite the limitation, this article provides ample insights to see where we are situated at the moment regarding the convergence, if it would happen, with industrial performance data.

2. Theoretical Backgrounds

2.1 Convergence of Technology

2.1.1 Concept of Technology Convergence in This Research

As economies get complex, technology side has reacted by deepening its original realm as well being connected to seemingly unrelated fields, which has been expressed in technology convergence concept [3,4]. In discussing the early ideas of convergence [5,6], as shown in Table 1, it was possible to consider two conceptual typologies of convergence. The first type of technology convergence is found across technologies, which includes convergence between basic and applied technologies as well as convergence between different applied technologies. The second type is technology convergence across industries [7,8], which includes convergence between and among neighboring sectors as well as convergence between and among non-neighboring sectors. As for the examples of the technology convergence across technologies, in automobiles, it is an inescapable trend that more & more micro processors are being equipped as the basic specification[9, 10]. Following the trend, telematics required for automobiles would increase the need for the convergence between mechanical & electronics technologies [11,12].

With the above idea, it is possible to show two possible tracks of convergence across

Table 1. Examples of Convergence types

[Type I] Technology Convergence across Technologies	Convergence between basic and applied technologies Convergence between applied technologies
[Type II] Technology Convergence across Industries	Convergence between & among neighboring sectors Convergence between & among non-neighboring sectors

Table 2. Examples of Convergence type I

	Examples
[Type I-1] Between Basic and Applied Technology	Bio-Chemical technology, Quantum physics and IT Nano technology and its applications
[Type I-2] Between Applied technologies	Robotics,Telematics

technologies. Type I-1 shows a track of technology convergence between basic knowledge & technology and applied technology, with examples ranging from the LCD (Liquid Crystal Display) case to the Quantum physics and its application with IT[13] as shown in Table 2. The examples of Type I-2 will be Robitics and Telematics refers to the convergence of telecommunications and informatics.

2.1.2 Academic Discussion Preceding the Convergence Arguments

Fordism, post-Fordism, FLSP, lean production

As for the way of organizing technology and industrial sectors, theories of production modes were introduced and settled down as a management theory. Fordism is another way of calling mass production system[14, 15]. After being developed by the Ford company, it has been widely adopted after the World War II all over the globe. Fordim can be signified by a single manufacturing to aim at the economies of scale it intends to achieve[16,17].

In comparison, scholars in the 1980s rediscovered an alternative production mode, called the flexible specialization, which was inspired by the guild type small scale production in Europe[18]. In a modern version, what this signified is that the production system is geared toward the economies of scope[19,20]. Under the principle, contrast to the economies of scale, small quantity for each item and wide & related product lines are the key features. One interesting insight has been neither of the two can overwhelm the other, which means they will have to co-exist in a dualism[21,22]. In between the two modes, a hybrid variant came in the name of post Fordism, which include different naming including the lean production.

The significance of the discussion to the topic of this research is that if convergence is found in one of the country data sets and not from others, a discussion for the future will be remaining on whether the remaining countries will feature the convergence in the future like that of following the “flying geese model”[23,24].

2.1.3 More Realistic Public Appeal

Compared to 1990s, 2000s, ad 2010s, this decade of 2020s has seen more vivid picture or symptoms of technology as well as industry convergence[25,26]. One typical example would be auto industry. While traditional auto industry using internal combustion engines would have a collection of mechanical sector as the main, with electronics sectors has been a growing component of values adding, a newer electric car industry eptitomized by Tesla and others would have electronics sectors as the main with traditional sectors like metal as a sub components sector[27]. From public 's point of view, this is an unshakable evidence that auto industry is being changed[28]. Getting into a more tangible discussion and focusing back into the research scope, this paper is targeting a more focused across industry convergence and its tracks. Auto industry, for example, was primarily mechanical engineering dominated, which can be interpreted as the sector where machinery and steel industry take the prime roles, while rubber, plastics, and electronics take partial roles of their own. In comparison, the hallmark of the electric cars, Tesla, when one sees it, is basically electronics and batteries oriented, and steel and plastics & rubber take the partial roles. If this could be understood as a paradigm shift, then it should be found in any of the industrial, economic indicators to show the change of terrain in auto industry[29].

Against this public appeal, academic and more serious research tradition should answer by providing a better 'resolution' giving evidence regarding the convergence. This is exactly what this paper is geared toward.

2.2 Technology Life Cycle Argument

Technology life cycle theories have been floushing as a way to explain a very easy understanding of the stages of technology from introduction to the phase out or demise in the market. One of the well known TLC

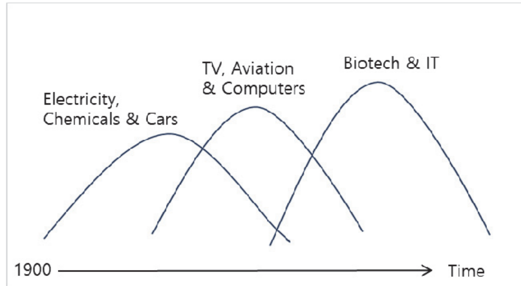

Fig. 1 Typical waves of Technology Life Cycle theory

models will feature "flying geese model", which implies that the future of following countries is what advanced country is today[30].

In some sense, technology life cycle theories have been mundane, and used mainly for basic insights and education. Yet, a more recent model, like the Gartner group's Technology Adoption Life Cycle Model, can extend the value of the TLC models[31,32]. The model tells us that whenever a new technology enters, public gets enamored by it and shows excessive attention, which will be followed by a breaking of the gust from excessive attention, and then it will go through a more stabilized "plateau" during which the technology finds robust application fields[33].

Applying this dynamic into this case, convergence has been a key word right after the 4th revolution concept was introduced, and it was easy to find relatively easy example like the electric cars. As time goes on, public attention wanes, and now it is time for researchers and industry experts to find out how data can present some evidence of the changing industrial and technological landscape. The model implies

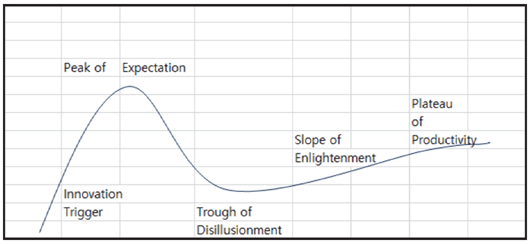

Fig. 2 Gartner Group's Technology Hype Cycle Model

that it takes some time until the maturation and adaptation of the technology is attained, and meanwhile public's spotlights can be waned, which is not only natural, but also an inescapable phenomenon[34].

As shown in Fig. 1, according to Gartner Group's Technology Hype Cycle model, the process of a new technology being introduced and maturing is explained in five stages. 1) Technology Trigger: the stage where a new technology gains attention, 2) Peak of Inflated Expectations: the stage where exaggerated expectations are formed, 3) Trough of Disillusionment: the stage where disappointment with the technology arises, 4) Slope of Enlightenment: the stage where realistic understanding is established, and 5) Plateau of Productivity: the stage where the technology is widely adopted and commercialized.

3. Methods and Data

3.1 Numerical Taxonomy: Its Operational Definition

This research employs time series tuned Cluster analysis as a method of numerical taxonomy to track any evidence of industrial convergence[35]. While conventional cluster analysis is well known for its information-summarizing capacity, when used with time series data will process the annual rate of change. In this research, two types of times series data were utilized. One is industrial wage data, while the other alternative is annual research and development investment in each industrial sector. For both data, annual change rate is calculated to perform time series tuned cluster analysis or numerical taxonomy[36]. The aim of cluster analysis in this research is to find a structure of industries based on similarity of cumulative annual change rate of the data series in anaylsis.

In comparison to the traditional economic approach that is bound to the traditional Standard Industrial Classification (SIC), in which new technology trend expressed in closeness of technology used can not be updated annually, the time series based cluster method is a sensitive mechanism to reflect the changing industrial landscape [37,38]. If unrelated industrial sectors, in SIC codes or conventional understandings, turned out to be closely located to each other in the cluster results, research tradition this research is subscribing would infer that symptoms of convergence may occur in these industrial sectors [38,39].

Regarding the use of wage data and R&D investment data, there are theoretical as well as practical reasons. Wage data of industries (basis: SIC codes) is an indirect measure of industrial competitiveness, yet this feature has an unmatchable forte in the sense that the data would not be distorted by economic, political contexts[40,41]. That is why wage data has a back-up by Economics as the ground for "Industry- Rents", which explains why common worker at Google can be paid more than excellent worker at a third-tier IT firm[42,43]. Despite this advantage, good wage data is hard to get, and cross country comparison could be limited. To compensate this, this research employed R&D investment data(basis: SIC codes), where it was applicable and pertinent. Although there are pros and cons for each data type[44], they are sufficiently useful in tracking the potential closeness as a proxy for the convergence [38,45].

At the last part of this research, if arguments on the convergence can be extended, then it may be a sensible idea to suggest a re-writing of the SIC codes based on the earlier evidence of technology convergence. SIC codes are fixed like laws, while numerical taxonomy results are like living things. Thus, an alternative would be a revision of the SIC system by adding "tails" to express convergence traits. It would be sensible because fundamental revision of the SIC would not feasible due to cost and institutional inertia including convenience.

Now, take a look at the Procedures for Time-series based cluster analysis can be presented in the following lines.

Based on the calculated annual change rates, this research launched a numerical taxonomy with time-series based cluster analysis. The reason to be called as numerical taxonomy comes from the traits that change pattern of industrial sectors would determine which sectors will be grouped in separate groups [46].

Numerical expressions for the time series tuned cluster analysis can be presented as follows.

Stage 1: Average Rates

Begin with an NxT matrix R of average rates(or comparable performance variable) for N officially-defined industries for years t=0 to T. (3 digit SIC codes are typically used.)

Stage 2: Convert to Time Series Data

Convert to an Nx(T-1)=NxP matrix G whose elements git are the rates of change of the performance variable for i=1 to N industries for years t=1 to T. Each row g is therefore a time-series of rates of change.

Stage 3: Clustering Method

Cluster the rows of G according to the Euclidean distance[47] $D=\sqrt{(\Sigma t(git-gjt)2}$ criterion using Ward's method(a hierarchical agglomerative procedure that minimizes with-in-group variance relative to between-group variance at each step). This research adopted the Ward's method in order to maximize between group variance and minimize within group variance[48,49].

Step 4: Grouping

Choose an appropriate level of grouping based on the agglomeration schedule and marginal loss of information as clustering progresses. That is, stop clustering at K groups when the algorithm starts forcing dissimilar objects into awkward and unwieldy clusters.

3.2 A Meta Analysis Approach

This research utilizes different data sets from three countries, some from industrial wage, and others from industrial R&D data. While using and integrating these data sets and analysis, it was though to be sensible to have a meta analysis perspective, in which an overlooking insights are added in addition to the micro level individual analysis.

3.3 Data

As for data, this research employed two types of data: wage data as indirect measures and as direct measures of R&D investment data. For the Korean data, the Occupational wage Survey by the Ministry of Labor (1971-1998) was used, while for the Japanese source is the Wage Section of the Annual Statistics by the Bank of Japan(1961-1992) was utilized. As for the wage data, comparable wage data sources of Japan and Korea are used as an indirect ,but unbiased measures of industrial & technological change, following examples in academic circles. For the U.S. data, the data of the National Science Foundation (NSF) R&D data(1958- 1998) and a more recent 2010-2019 data was used.

Due to data limitation and availability, the three countries have slightly different time frame for analysis. This research takes the U.S. data sets of both periods 1958-1998 and 2010-2019 as the reference basis, because this data is direct R&D time series data, and if we can find some tracing records of convergence, other two countries' data can be used for comparison purposes. Of course, R&D data for Korea and Japan could be found elsewhere, which will be left as a future task, the choice of data in this research has its own merits for the following reasons. Economics, including labor economics, has been teaching its theory of "industry rents", which argues that wages reflect competitiveness of the industrial sector and its technology and at the same time wages are not biased or over blown in different packaging. "Not biased" means relatively immunity from profit and tax and other socio economic practices. "Not overblown" means that unlike other science and technology policy measures, wage data is more transparent.

With these merits, what this research is claiming is first, if wage data based time series clustering can glean comparable results vis-à-vis R&D data based results, then we can be sure that the findings from the R&D data is robust. Second, if both direct R&D and wage data can offer meaningfully comparable results and implications, then we can have leave this as the future research agenda to find which data is more precise in tracking the convergence. Third, if the two types of data can be somewhat compatible with each other, it can be an alternative source for those countries where one type of data set is not available.

4. Research Findings

Implementing the tile series tuned cluster analysis of the three countries resulted in the followings.

4.1 Cluster Results from the Korean Data (1971 ―1998)

4.1.1 Cluster Grouping

The Korean data set provided the following clustering results (see Fig. 3).

Group 1(13): Transportation related service, other petroleum, retail, finance service, electricity & gas service, insurance, Construction, wholesale, scientific measurement instrument, social service, metal assembly, printing, metal mining

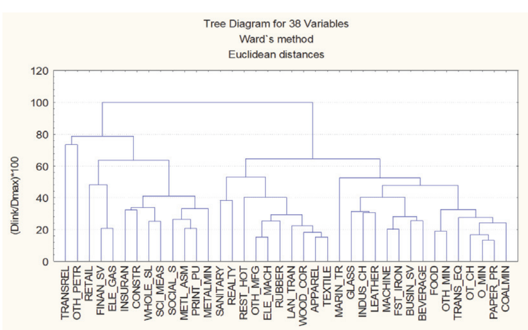

Fig. 3 Cluster map of the Korean industries 1971-1998

Group 2(10): realty, sanitary service, restaurant/hotel, other manufacturing, electrical machinery, rubber, land transportation, wood, apparel, textile

Group 3(15): marine transportation, glass, industrial chemical, leather, machine, first iron, business service, beverage, food, other mining, transportation equipment, other chemical, other mining, paper product, coal mining

4.1.2 Implications

From the Korean case, several points can be raised. First, due to data period, it was not possible to expect the convergence tracing among industrial sectors. Second, what was so clear was the characteristics of Group3, which was the results of the Korea's heavy industrialization drive in the 1970s, the so called the HCI(Heavy and Chemical Industrialization). Third, Group 1 is a high flyer service sectors concentration, while group 2 is a light industrial sectors and other service sectors, with an exception of the electrical machinery sector.

4.2 Research Findings from the Japanese Data

4.2.1 Cluster Grouping

The Bank of Japan data of 1961-1992 has yielded the following clustering results (see Fig. 4).

Group 1(9): Machinery, Iron/ Steel, electrical machinery, fabricated metal, precision equipment,

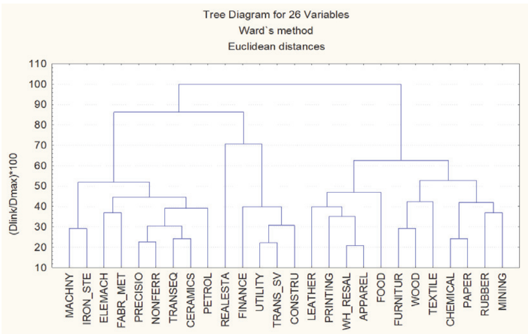

Fig. 4 Cluster map of the Japanese industries 1961-1992

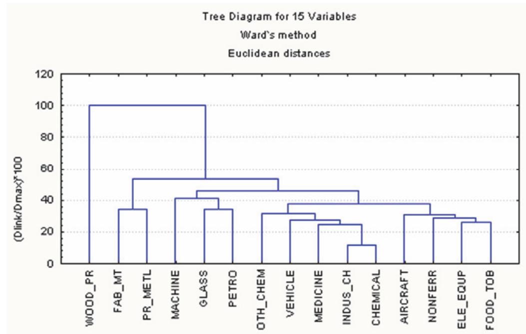

Fig. 5 Cluster map of NSF data on the U.S. R& D from 1958-1998

Nonferrous metal, Transportation equipment, ceramics, petroleum

Group 2(5): Real estate, finance, utility, transportation service, construction

Group 3(5): Leather, Printing, Whole sale, Apparel, Food

Group 4(7): Furniture, wood, textile, chemical, paper, rubber, mining

4.2.2 Implications

The Japanese clustering results suggests several implications. First, it shows a very strong manufacturing sector concentration in group 1, while group 2 is a service sector concentration. Second, data period will not allow to see the potential convergence in the figure. Instead, it shows Japan's strong manufacturing forte that has been formulated over the 30-40 year period.

4.3 Research Findings from the U.S. Data (1958-1998)

The 1958-1998 U.S. data implicitly gives a three group structure with an outlier of wood product sector. As shown in Fig. 5, from left, Group 1(2) is a sector segment of fabricated metal and primary metal industries. Group 2(3) is made up of machinery, glass, and petrochemical sectors. The prime group(9), which is the largest and has two subgroups, ranges from other chemical, vehicle, medicine, industrial chemical, and chemical sectors to aircraft, nonferrous metal, electrical equipment, and food & tobacco sectors.

What catches one's eyes are, first, a concentration of core manufacturing sectors is evident, while there exists a sub grouping, one with vehicle, the other represented by aircraft respectively. This group 3 has been reigning the industrial landscape as well as R&D of these industries during the 40 year period. Second, we can trace some early signs of convergence in the sense that deeply related technologies and their representing sectors are closely related in the grouping structure. For example, aircraft is located near to nonferrous metal, which represents the sector that can produce aviation related material as well. Also the aircraft sector's close location with the electronics and electrical equipment shows that R&D pattern and growth showed covariance in the sectors. Likewise, medicine, industrial chemical, and chemical sectors are not only close in nominal SIC systems, but also featured similar growth pattern of R&D growth.

Despite these early symptoms of technology convergence, what was lacking in the 1958-1998 data was the convergence across sectors, with a weak but solid exception of the aircraft sector, which could be viewed as the harbinger of convergence.

4.4 Research Findings from the U.S. Data (2010-2019)

The cluster grouping result from the 2010-2019 data shows somewhat different in the sense that it shows more vivid symptoms of technology as well as industrial convergence. Before going into the analysis, this research can report a grouping structure of 3 groups.

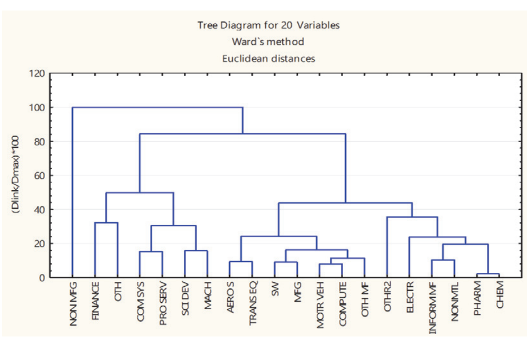

Fig. 6 Cluster map of U.S. R&D from 2010-2019

Group1: Finance, communications systems, professional service, scientific development service, machinery

Group2: Aerospace, Transportation Equipment, Software, Manufacturing, Motor & Vehicle, Computer, other manufacturing

Group3: Electrical manufacturing, Information Manufacturing, nonmetal products, Pharmaceutical, Chemical

Regarding the symptoms of the convergence, several key findings can be reported. First, aerospace and transportation equipment, and software sectors are in the vicinity, and motor vehicle and computer sectors are very closely located based on the time series cumulative movement of data trends. All these four sectors are also in the same group 2. Second, one can find that in group 3, information machinery and electrical machinery sectors are closely located, while pharmaceutical and chemical sectors are also close neighbors. Third, group 1 also shows, although weak, some signs of convergence in the sense that machinery sector is located near to scientific development, professional development, and communication systems. It can be inferred carefully that machinery sector included in group 1 could be showing convergence with some of the advanced service segements and also could be non-high flyers among machinery industries in the sense that they are not the focal points of the 4th revolution.

5. Discussion

5.1 Insights from the use of R&D Investment Data(Direct measure)

Insights from the U.S. data is striking. While 1958-1998 data period did not present impressive outcomes of the 4th industrial revolution tracing, the 2010-2019 did. When we look at Group 2 which has vicinity of Motor vehicle and computer sector, closeness of Aerospace, Transportation equipment, and software. This is, in fact, Phenomena Tesla! It is the symptom and tracing of the 4th revolution in the sense that i) de facto electric car ecology is shown, ii) aero space, trans equipment, and software are all driven by software side in their dynamics. Close location in time series tuned cluster tree means that they are growing in a very similar way. No evidence can be clearer than this result.

In comparison, 1958-1998 U.S. data has shown much stabilized and mundane industrial landscape before the 4th revolution. Vehicle and aero space are respectively well trenched in their own position.

5.2 Insights from the use of Wage Data(Indirect measure)

There as always been some dilemma of choosing between direct and indirect measures of industrial competitiveness. Economics has strongly supported the latter. Despite this pros and cons, at least, in this research, indirect measure of wage data also presented industrial landscape quite comparable to the direct measure of R&D investment. In the massive Korean data set, it was not feasible to find the tracing of convergence, due to time period as well. What was striking was the tracing of the Korea's Heavy and Chemical Industrialization of the 1970s, which brought the industrial landscape of the country today, was evident. Group 3 of Korean data is a concentration of all the HCI big push investment. It is fascinating to observe how Korea's traditional manufacturing industries, such as the steel/shipbuilding, automotive, and semiconductor sectors, can integrate with the transformations of the Fourth Industrial Revolution, particularly through the technological convergence with Artificial Intelligence and Advanced Manufacturing Technologies (AMT).

In comparison, Japanese data also showed the economy's traits so well. Due to data period, it was not easy to capture the tracing of the 4th revolution, yet the data clearly showed the concentration of the country's strong manufacturing sectors in group 1.

6. Conclusions

Through the pages, this research has explored to see whether tracing of the 4th revolution, i.e. industrial convergence, can be presented with data analysis. As the preceding section has just reported, the U.S. case of 2010-2019 data presented a clear tracing of the 4th revolution. One might ask how can one take this finding? A partial clue comes from the logic "Critical case study" by John Goldthrope. He tried to show that wealthy factory workers will feature the embodiment of their way of thinking by choosing the most well-developed industrial district of the 1960s U.K., Luton. His assumption was that if the most affluent workers are maintaining what they have in common, then it is very likely that less affluent workers in other regions will take more time, at least to have their attitudes changed.

Likewise, although limited in the U.S. case, it would be reasonable to assume that convergence tracing will be found in Japan and Korea if and only if comparable data sets are used again. This also signals the efficacy of the"flying geese" model of TLC(Technology Life Cycle) model, in which follower countries' future is what advanced country's presence in a simplified way. Learning from the implication of the cases of the three countries, it may be a lon term discussion agenda to amend the standard SIC system, not in a way for a total change, but by adding appendix type digits at the end. This is to minimize the currently established system widely used worldwide, yet to reflect some tracing capacity for the convergence discussed in this research. In that case, a typical SIC code example should be SIC 312-abc, where the abc could be numerics that reflect characteristics for convergence.

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