Double-Loop Bench Marking Methods in the Era of Data Deluge: An Empirical Scientometric Study and Assessment of Japan's *Galapagos Syndrome* in Scientific Research Activities

Nobuyuki Shirakawa[1], Takao Furukawa[2], Kazuhiro Hayashi[3], Masatoshi Tamamura[4]
[1]Technology Strategy Center, NEDO, NISTEP, IFTECH and Keio University, Tokyo, Japan
[2]Faculty of Home Economics, Kyoritsu Women's University, Tokyo, Japan
[3]Science and Technology Foresight Center, NISTEP, Tokyo, Japan
[4]Faculty of Policy Management, Keio University, Kanagawa, Japan

Abstract—**This paper addresses the need for reliable measurement guidelines for organizations or entities in the turbulent environment of our era of data deluge. Based upon conceptual and empirical research in bibliometrics, we suggest an analytical approach to benchmarking the technology management of surprising and potentially damaging phenomena. In order to do so, we propose a method called "double-loop benchmarking," which consists of two steps: (1) structural benchmarking, based upon social relationships between actors and actants, and (2) projecting transaction data accumulated through daily business processes as benchmark indicators based upon the social relationships empirically measured in the first step. This paper can be seen as part of a broader agenda for how to manage during continuous but unpredictable change in circumstances of open ignorance. As an empirical study in bibliometrics, we propose a methodological improvement in scientometrics using data repurposing and triangulations. An international comparative analysis reveals empirical evidence that Japan's dynamic technology portfolio on research activities in the fields of electrics, electronics, information, and communications has consistently deviated from that in global trends since the 1990s. This phenomenon, which may be described as the "Galapagos Syndrome," is a strategic pitfall under the dynamic technology paradigm change.**

I. INTRODUCTION

Though no data source can be assumed free of biases, balancing sources of information can help to reduce overall forecasting bias. Questions about the theoretical significance of indicators and their limitations in using various databases and indicators indicate the necessity of exploring more systematically the relations between quantitative methods and qualitative social inquiries.[1]

In scientometrics, the main problem is that, on the one hand, there is a set of indicators, techniques, and databases concerning the sciences and, on the other, sociological theorizing that cannot easily be fit into models that are operationalized and tested using scientometric data and related techniques [17]. For example, in scientometrics, aggregated journal-journal citations are considered a high-level structure for creating "maps of science" [20]. Though one of the most widespread myths in scientometrics is citation analysis, the historically continuous discussion that calls for a theory of citation in quantitative science studies gave rise to the necessity of alternative metrics: altmetrics [21]. This alternative led to the creation of a new metrics based on the Social Web, which was analyzed and which led scholarship towards e-science. In altmetrics, scientific impact is measured through repurposing transaction data via the social web—that is, downloads, storage, links, and bookmarks.

The assumption of the conceptual stability of terms over texts is more problematic than is often thought in everything declarative: knowledge engineering, thesaurus construction, and indexing. This bias, called the "indexer effect" in bibliometrics, is a highly significant concern in the generation of artificial intelligence and co-word relations among scientific texts. Some of its peculiarities are as follows [17]:

1) The indexer is not a practicing scientist [26].
2) The selection of documents creates an additional effect at the level of the aggregated document set in which similar words may have different meanings at different moments in time, and may represent different theoretical perspectives phenomenologically.
3) The previously signaled packing of the database in an index creates a first (mostly intuitive) taxonomy; therefore, any further clustering is, by definition, "clustering the clusters."

This "clustering the clusters" problem in the analysis of bottom-up approaches is a reflection of the cognitive-capacity limits of the researcher, with or without detailed knowledge on the context. Reasoning-as-cognition has a crucial holistic component that cannot be implemented in algorithms [10]. Reasoning can be "abstracted from the mind" and programmed into algorithms [24].

To cite a case of co-citation analysis without using indexes, the scientist performs indexing without being a practicing scientist in order to evade bias in the data processing and to obtain more detailed technical computation in the analysis or observation of the results. As a result, researchers become more ad hoc or intuitive in their interpretations—ironically, because of the restricted rationality resulting from their cognition limitations. Thus, avoiding such a cognition bias program in relating data is extremely rare not only in bibliometrics but also in other research across all fields, which uses voluminous data extracted from a database.

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In this article, as an empirical study in bibliometrics, we propose a methodological improvement in scientometrics for technology planning using data repurposing and triangulations. We offer an analytical approach called "double-loop benchmarking" to create indicators for technology planning, in order to cope with a surprising and potentially damaging phenomena in the data deluge [2]: the era of "big data" [27]. An international comparative analysis reveals that empirical evidence that Japan's dynamic technology portfolio of research activities in electrics, electronics, information, and communications has consistently deviated from global trends since the 1990s. This phenomenon, which can be described as the "Galapagos Syndrome," may be regarded as a strategic pitfall under the dynamic technology paradigm change.

II. METHODOLOGY

A. Actor networks theory (ANT) and data structure

In actor networks, the structural differences among social, cognitive, and natural units are explicitly denied. It is postulated that each node of the network can be composed out of another similar network [6, 7]. An actor network, for example, may consist of oceanologists, who try to transform fishing into "aquaculture"; the science of oceanology that imposes a problem formulation; the fisherman who defend their interests; and the scallops that breed and swim in the networks. These actors and *actants* are defined with reference to a specific issue, commonly by a relationship of equivalents. Although such an arrangement seemed novel until the theory was commonly accepted, from the perspective of data structure and information processing, this model is extremely natural. Transaction data, accumulated electronically about a routine with a protocol on a specific issue, generate an enormous quantity of semi-structured data. These data reflect the link structure that actor and actant weave.

B. Assessing index calibration methodology

Argyris [1] proposes double-loop learning theory, which pertains to learning in order to change underlying values and assumptions. The focus of the theory is solving complex, ill-structured problems that change as problem solving advances. An important aspect of the theory is the distinction between individuals' espoused theories and what they actually do: bringing these two into congruence is a primary concern of double-loop learning. Typically, interaction with others is necessary to identify the conflict.

Our holistic assessment design for double-loop benchmarking that enables naturalistic inquiry obeys the qualitative research code of conduct to classify existing aggregate data into context-specific categories by conducting critical case sampling and purposeful data sampling as benchmarks. Furthermore, an additional self-calibration tool is equipped with a simple vector space model, which can enable an analyst or stakeholders to deliver a signal to learn to rectify underlying values and assumptions.

Patton [19] asserts that four dimensions of triangulation—methods, sources, the analyst, and theory perspective—can support qualitative analysis verification. To perform empathetic naturalistic inquiry, we combine the following four triangulations in the process of data aggregation and assessment, and demonstrate, using the principles, how to make them more directly applicable to technology planning: we divided "double-loop benchmarking" into two steps: (1) structural benchmarking and (2) data projection and its assessment.

1) Structural benchmarking

In structural benchmarking, we define a benchmark community related to the subject/issue prior to setting specific a priori indicators for benchmarking. A target community is used as a meta-benchmark to measure the social relationships within actor networks.

2) Data projection and assessment

We repurpose transaction data accumulated through daily business processes to benchmark indicators by projecting it onto the social relationships empirically measured in the previous step. We set context specific indicators to make an assessment, not to employ a d-hoc gained data.

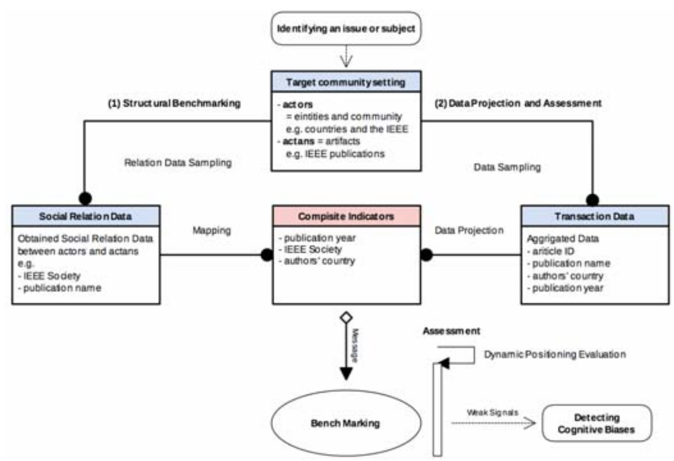

Fig. 1 Double-loop bench marking methods

C. Data processing: An example of an empirical scientometric study

Hereafter, the methodology proposed above is demonstrated through an example to show its usefulness and the detailed procedure involved in data processing.

1) Identifying an issue or subject: Technology trends in Engineering

In engineering, especially in computer science and electrical engineering, it is difficult to grasp the whole picture of the specialized field from the retrieved information based upon the index or keyword. This difficulty arises because Web of Science and Scopus still have shortcomings with regard to indexing articles in computer science and electrical engineering compared to how it handles articles in physics and mathematics [25].

This study examines the nature of electrical and electronics (E&E) and information communication technology (ICT) research, and identifies the global shifts that have occurred in publication activities under the assumption that a definite correlation exists between research activities and publication activities.

2) Target community setting: IEEE as an engineering technical activities community

Assuming a definite correlation between research and publication activities, this study analyzes these factors at the Institute of Electrical and Electronics Engineering (IEEE), the world's largest professional engineering association and engineering publisher. As the IEEE is responsible for a high percentage of all publications in the engineering field and thus has a great quantitative impact [22, 23], the organization has a large effect on science linkage [4]. In the quantitative and qualitative analysis of the impact, this data-intensive, within-case study analysis focuses on the coverage and impact of IEEE publications in scientific publishing, as well as the structure of its Societies and Technical Councils. These Councils are IEEE sub-communities that pursue interests and address concerns regarding technical activities within certain specialized areas.

TABLE 1: COMPENDIUM OF SAMPLED DATA ON IEEE PUBLICATIONS

Publisher **IEEE**	**Years** *(Base)*	**Number of Articles** *(publications)*	Classification	Notes
Periodicals	From 1980 to 2008	355,891 (201)	Categorized by Sponsorships	18 Journals, 114 Transactions,
Journals and Magazines	Published year		38 Societies and 9 Technical Councils	69 Magazines From 141 countries/regions

3) Data sampling and obtaining social relation data individually

The official IEEE database, referred to as IEEE*Xplore,* is indexed using metadata from the *Inspec* database. Therefore, the metadata was extracted from *Inspec*, which comprised approximately 355,000 periodical articles, to assess the coverage of the data by IEEE*Xplore* at the end of February 2010. We were able to conduct data sampling with high precision (more than 98.7%) from IEEE's daily publication of business transaction data with ease. Then, the relational data on journal sponsorship from IEEE*Xplore* was extracted individually.

For the articles published in certain academic journals, the number of articles in Country k in Year t published in Academic Journal j became $X_{jk}(t)$. These elements were placed in the matrix X(t). When the relation between Society i and Academic Journal j is expressed in Matrix A—the Matrix Y(t) containing the elements of the Number of Articles $y_{ik}(t)$ of Society i that are classified into Country k—the variable is defined by the following formula:

$$y_{ik}(t) = A\, X_{jk}(t) \qquad (1)$$

(a) Data projection to make indicators for a specific social relation

Each of the $Y_{ik}(t)$ elements in row k of Y(t) (I = 1,2,…,n) expresses the number of articles per year for Year t for each society—that is to say, for each area classified into Country k. This column vector $y_i(t)$ is assumed to be the technological position of the country.

The development of a Society is a historical process; thus here, with the criterion of whether or not there was some sort of sponsorship (*i.e.,* that undertook cost of publication or other forms of cooperation, such as peer review) for a periodical in 2008, the components of Matrix A were established based on the results of a search in IEEE*Xplore*. In the event that Society i has sponsorship for Academic Journal j, Aij, which is the ij element of A, is assumed to be 1. When multiple Societies have sponsorship (co-sponsorship), as it is assumed that the multiple elements aij of row i are 1, the result of adding the total number of articles from each Society is greater than the actual number. The articles were categorized into specialized fields that corresponded to the fields represented by the Societies and Technical Councils.

(b) Dynamic positioning assessment

From the definition of technological position yi(t) for Country i in Year t, the dynamic technological position yw(t) of the entire world is expressed in the following formula:

$$y_w(t) = \sum_{i=1}^{n} y_i(t) \qquad (2)$$

4) Dynamic position assessment within the benchmark community

Based on technological position yw(t) of the entire world and technological position $y_i(t)$ of Country i in Year t, we are provided with a definition for technological position $P_i(t)$. This position is defined as an indicator that, for a certain year, shows the similarity of technological positions between the world and Country i. As the cosine of the angle that performs $y_w(t)$ and $y_i(t)$, the dynamic technological position $P_i(t)$ is expressed as follows:

$$P_i(t) = \frac{y_w(t) \cdot y_i(t)}{|y_w(t)\|y_i(t)|} \qquad (3)$$

III. RESULTS

A technological paradigm change was observed from the IEEE in the form of indicators that reflect a specific technological trajectory and changes in the technology paradigm among the IEEE's societies with regard to the sponsorship of journal articles. Echoing these changes, the IEEE society is adopted as the indicator of the unit of analysis in a specialist field as shown in Fig. 2. The figure shows the number of periodical articles published by the IEEE societies in descending order. The number of articles in IEEE publications clearly reflects trends in technical activities by specialized field, with a shift in the leading society occurring approximately every five years. The dominant field in each era can be described as follows:

I. **Early 1980s:** nuclear science
II. **Late 1980s:** magnetics and electron devices
III. **Early 1990s:** electronic devices, photonics, and computers
IV. **Late 1990s:** computers and communications
V. **2000s:** networks, wireless communications, signal processing, and computers

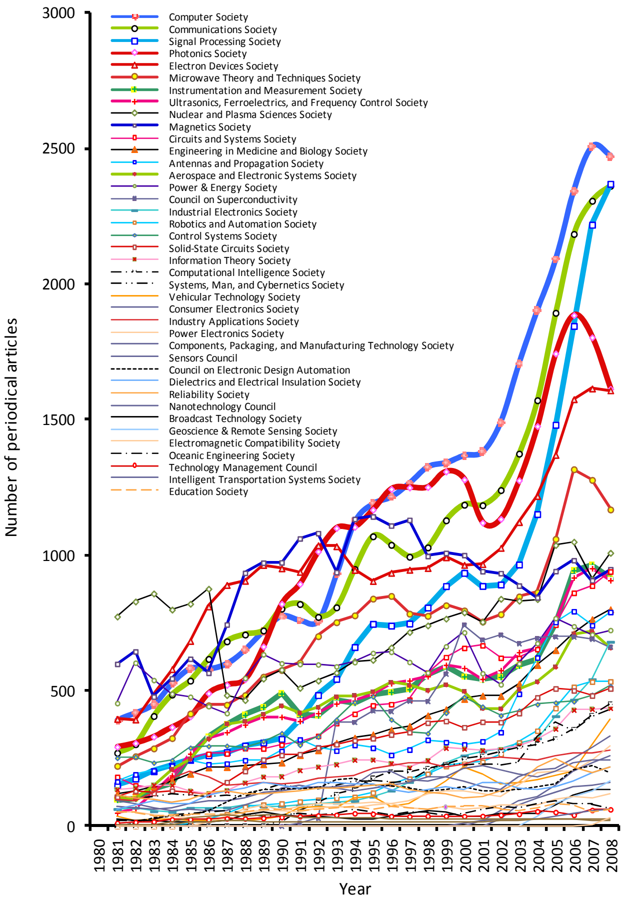

Fig. 2: Number of articles published by societies globally (1980–2008)

A. Validation and Implications of Methodological Superiority

Fig. 3 is a graph of research fields throughout the world and in Japan according to Inspec database sections. Japan has long had plenty of literature in physics and electronics but little in the field of information. Figs. 3 and 4 present graphs of research fields throughout the world and in Japan, respectively, by level 1 category classifications. The graph of the world shows an ever-increasing trend in the literature from all fields, a result of the bias in published data from the geometrically increasing academic literature that has resulted from improvements in the scientific establishment throughout the world. It is therefore difficult to observe dynamic technology changes as we have shown in our methodology.

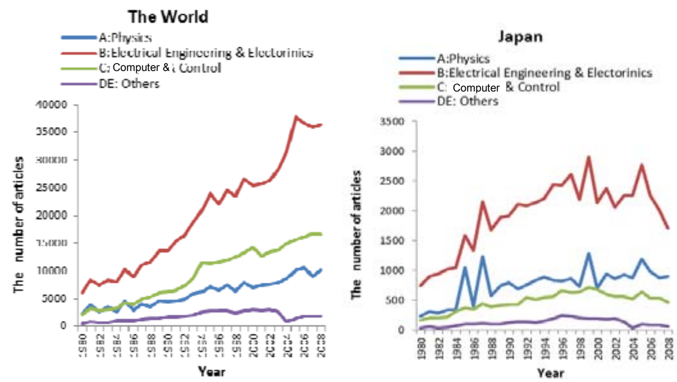

Fig. 3: The world and Japan by Inspec database section

Section A - Physics
A00 General
A10 The physics of elementary particles and fields
A20 Nuclear physics
A30 Atomic and molecular physics
A40 Fundamental areas of phenomenology
A50 Fluids, plasmas and electric discharges
A60 Condensed matter: structure, thermal and mechanical properties
A70 Condensed matter: electronic structure, electrical, magnetic, and optical properties
A80 Cross-disciplinary physics and related areas of science and technology
A90 Geophysics, astronomy and astrophysics

Section B - Electrical engineering and electronics
B00 General topics, engineering mathematics and materials science
B10 Circuit theory and circuits
B20 Components, electron devices and materials
B30 Magnetic and superconducting materials and devices
B40 Optical materials and applications, electro-optics and optoelectronics
B50 Electromagnetic fields
B60 Communications
B70 Instrumentation and special applications
B80 Power systems and applications

Section C - Computers and control
C00 General and management topics
C10 Systems and control theory
C30 Control technology
C40 Numerical analysis and theoretical computer topics
C50 Computer hardware
C60 Computer software
C70 Computer applications

Section D - Information technology for business
D10 General and management aspects
D20 Applications
D30 General systems and equipment
D40 Office automation - communications
D50 Office automation - computing

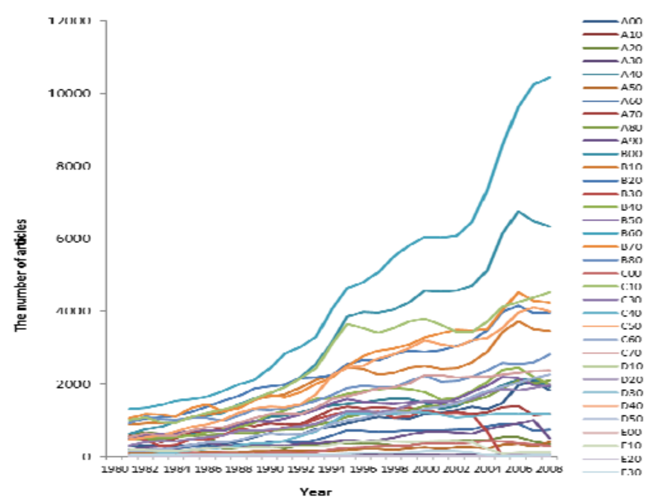

Fig. 4: Research fields throughout the world

Further, the graph in Fig. 5 is based on level 2 category classifications. When using this level of classifications, we can at last observe changes in technology paradigms at the same level as in our method.

From these results, we can assert that our methodology yields methodological validity for two measurements as well as strategic practical implications. Our method of analysis—using organizational relationships and technology management theory to process repurposed data—shows the effectiveness of the methodology and its potential for extracting significant knowledge, with less processing and calculation, by using the properties of huge amounts of existing data without vast amounts of professional indexing. The current issue in data science, processing semi-structured data with complex link structures, provides us with clues for discoveries that cannot be addressed if we use analysis that assumes distributions with independence between structured variables. Our method has potential as a new prescription for data processing within practical strategic research and as a way to generate strategic insights for technology planning.

An example: The code format is typically as follows: A = Physics, B = Electrical Engineering and Electronics, C = Computers and Control, D = Information Technology for Business, and E = Production, manufacturing, & mechanical engineering.

The code format is typically expressed as A7865K, where

A = section of the database
7 = Level 1: first order classification
8 = Level 2: second level of classification
65 = Level 3: third level of classification
K = fourth or most specific level of classification (not all codes have the fourth level of classification)

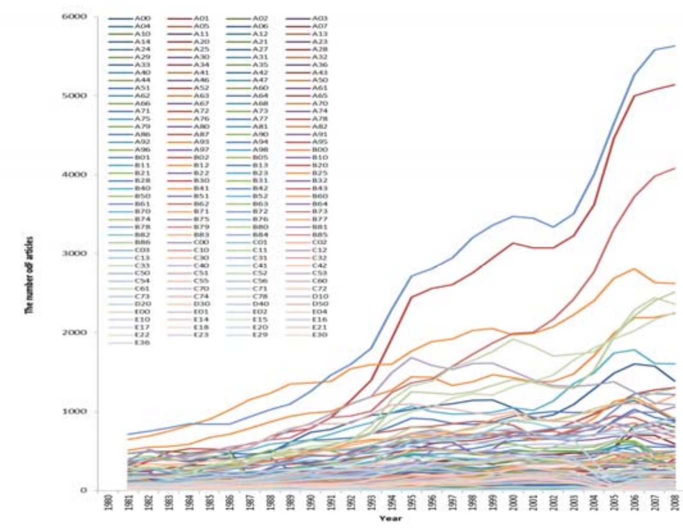

Fig. 5: Graph based on Inspec level 2 category classifications

IV. DISCUSSION

A. Trends in the number of articles in Japan and their structure

Fig. 6 shows the trends in the two-year moving average of the number of articles according to specialized fields between 1980 and 2008. Even for the total number of articles, the trend is different from the global trend, remaining flat over a number of years. Japan has maintained a structure for its research fields that includes many electric and electronic-related projects, and a small number of information and communications-related projects. The majority of fields have tended to maintain a fixed pattern.

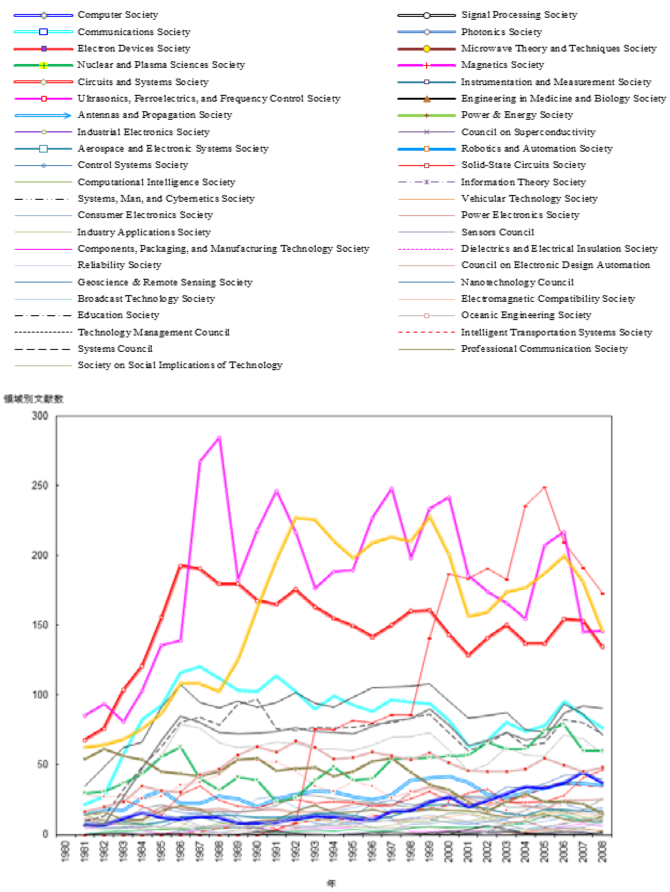

Fig. 6: Number of articles published by societies in Japan (1980-2008)

B. Dynamic technological positions

Fig. 7 shows global trends from 1980 to 2008 for technological positions in Japan and in other countries. In the preceding section, via re-targeting article data by using the relations between social groups with regard to journals, a change in the technological paradigm was clarified in an easy-to-understand manner. Here, Jaffe's [15] concept of technological position and an indexing method appropriate for a technological trajectory is used. For certain points in time, it shows the similarities between the global research portfolio of Japan and the portfolios of various other countries. If we compare the yearly trends of the similarities in dynamic technological positions among actors, it is possible to analyze chronologically Japan's global positions with regard to research in the electrical, electronic, and information and communications-related fields. In so doing, it is possible to verify whether trends in Japan's technological position have been deviating from changes in global research trends.

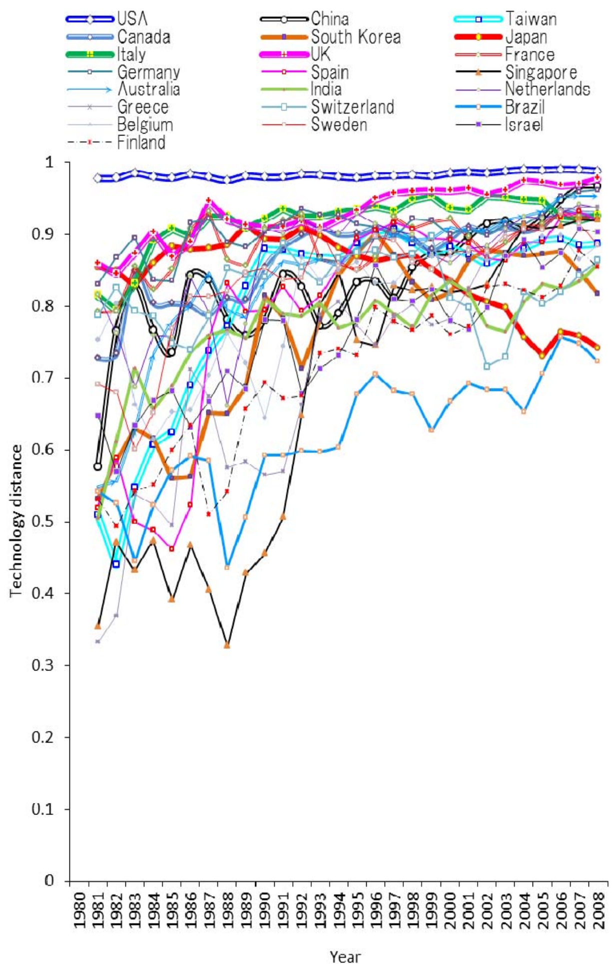

Fig. 7: Time series paths of dynamic technological position by country

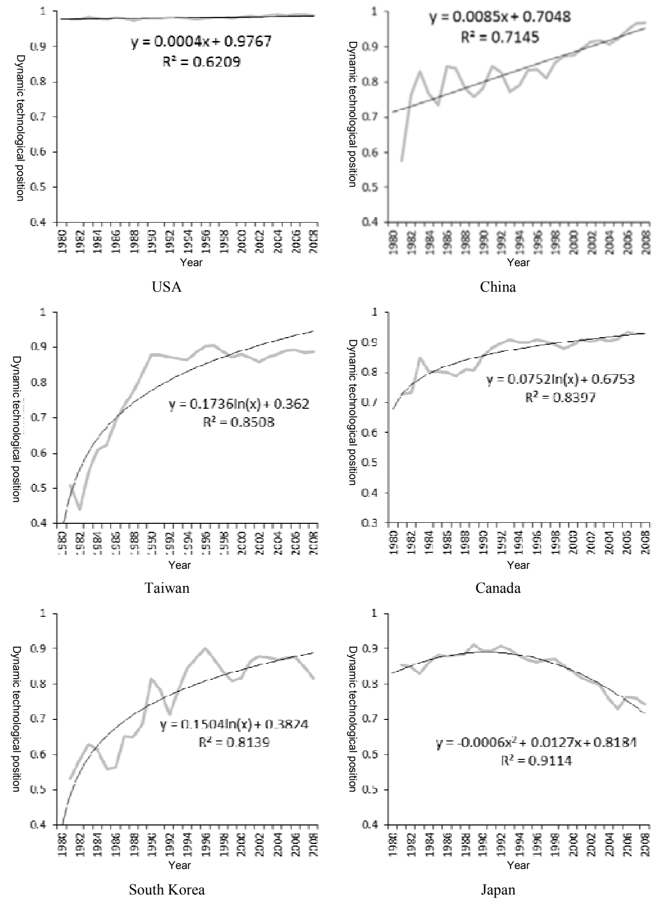

Fig. 8: Dynamic technological positions (1980–2008)

C. Comparative Analysis

Fig. 8 shows global trends from 1980 to 2008 in the technological positions of Japan and other countries and for regions in the United States, China, Taiwan, Canada, and South Korea. These nations and regions were selected because the number of articles they published in periodicals exceeded Japan's number in 2008. After calculating the technological positions for each year, the two-year moving averages are shown together with the approximation curves. The approximation curves for the five countries and regions other than Japan show that, for either a linear approximation or a log approximation, the approximation curves are applicable for the R2 coefficient of determination. As only Japan's curve was not applicable using either approximation method, the second approximation curve was used.

For the top six countries and regions, Fig. 8 shows the trends in the international share of each country for the number of articles published in periodicals in the 29-year period between 1980 and 2008. Several characteristics may be noted for each country and region.

The United States consistently shows no deviation from the global trend, despite the fact that its international share of articles declines by half. In other words, the changes in global research trends in IEEE as described in the previous section are the same as the changes in the trends in the electrical, electronic, information, and communications fields in the United States. This indicates that the United States leads the way in proposing new directions for research from within the changes during a given age, as expressed in its dynamic portfolio in the fields noted above, in which the USA has also become an international leader. China has been gradually climbing, and in 2006, it was ranked second in the world for its share of articles. It has been unifying its electrical, electronic, information and communications-related research with the rest of the world in terms of both quality and quantity. The oscillation in China's technological position has decreased since around 2000 and is converging at 1. Though this development is not completely shown in Fig. 5, this characteristic is shared by many of the countries that developed and grew in these fields from the second half of the 1990s onward.

The trend demonstrated by Japan, however, is different. Since the 1990s and during a period of more than 15 years, Japan's technological position has been consistently deviating from that of the global trend. Japan's share of article numbers in IEEE at the end of the 1980s approached its peak, rising to approximately 20%. After this, like the United States, its share declined; but unlike that of the United States, Japan's technological position has continued to deviate gradually away from 1.

D. Japan's Galapagos Syndrome as a communal bias of ignorance

The first aim of this study was to identify the shifts in the technology paradigm in the fields of E&E and ICT, using an eclectic and extensive approach inspired by qualitative research. The second is to evaluate and detect the trend in Japan's unique "evolutionary" deviation path known as the Galapagos Syndrome.

Japan's competitiveness internationally is not directly proportional to its world-class scientific and technological capabilities. According to the International Institute for Management Development [14], Japan is ranked number two in the world in terms of science and technology infrastructure. However, R&D is becoming less economically efficient, ranking particularly low in comparison to that of other developed nations. In a white paper on economics published in 2012 for the fiscal year, the Japanese Government noted that investment in R&D is not contributing to Japanese companies' operating profit. Thus, a conflicting situation has developed in which, on the one hand, Japanese companies and Japan as a whole have advanced in technological capabilities and have continued to develop high-performance products. On the other hand, however, all are losing international competitiveness. This phenomenon of an advanced technological evolution without benefit to either Japanese companies or to the enlarging Japanese markets has been named "the Galapagos Phenomenon" as a way of comparing it to the evolution of an ecosystem.

Japanese companies and the Japanese economy have gone through four different phases, starting with global success in the 1980s when the bubble economy emerged. Then, from the second half of the 1980s to the start of the 1990s, there was stagnation. While the Japanese "convoy-style" financial system approached complete malfunction, the soundness of its award-winning manufacturing industry and production systems were maintained. Currently, however, Japan's electronics industry, once the nation's prize industry, is losing international competitiveness.

Japanese electrical-appliance companies—such as Hitachi, Toshiba, and Nippon Electronic Corporation—have declined in comparison to overseas companies like the Samsung Group in South Korea. The latter possesses both capital and technological strengths; Taiwanese companies also, such as the Taiwan Semiconductor Manufacturing Company (TSMC), have solidified a business model with a vertical division of labor in the form of a foundry. Apple in the United States is another example of a business built on an original earnings ecosystem. The results of a survey on the decline of the Japanese electronics industry and affiliated companies have pointed to three problematic aspects: the business scale in the industry as a whole, the presence of excessive players in terms of company numbers, and the pursuit of high quality through superior R&D and technological capabilities. The third item requires searching for contributory factors in the shortfall of capability building, arising from business models as well as architectural factors, which have resulted in the loss of price competitiveness.

V. CONCLUSION

Ignorance is a significant source of technology forecasting bias, which in turn causes forecasting failures and disruptive surprises. Ignorance occurs when the outcomes are not known (or predicted). Another source of ignorance is a lack of information, which is another source of surprise in addition to the traditional economic concepts of risk and uncertainty. These can be categorized as either closed or open, and both types can be a key source of surprise [9]. Closed ignorance occurs when key stakeholders are either unwilling or unable to consider or recognize that some outcomes are unknown. In this case, the stakeholders have no knowledge of their own ignorance.

As a result, an evolutionary phenomenon of incompatibility, known in Japan as the "Galapagos syndrome" and at first appearing to be a unique evolution, has turned out to be a strategic pitfall. This pitfall is manifested in the recognition structure. As an example, consider the situation that prevails when management phenomena relating to Japan or Japanese companies are discussed. People often talk about the unique aspects of Japanese-style management. The problem is that this focus has been maintained whether the companies are succeeding or if their fortunes have suddenly fallen. In truth, Japan's specific management strategy as it relates to management theory is not exceptional. Thus, it can be said that in Japan, certain routines have been maintained within a set framework, and despite the fact that these routines have appeared to maintain a unique positioning, cross-referencing has demonstrated the coexistence of a seemingly mysterious phenomenon where dynamically changing contexts do not evolve and adapt from data with the same routines. The maintenance of routines in a dynamic environment has manifested as a phenomenon of incompatibility with a lack of recombination of organic resource compositions. At its height, Japan experienced evolutionary compatibility in its R&D activities, and because of that strength it entered a 20-year period of decline, commonly known as the "lost decades," because it never modified its resource base. Along with changes in technology paradigms, this analysis was able quantitatively to show the process of the gradual loss of compatibility.

The methodology here has adopted within-case analysis using the simple process of tracing and contextualized comparison, allowing for the performance of extensive bibliometric quantitative analysis on a specific social group and its subgroups by the simple quantification of its inherent organizational structures. This research quantifies dynamic changes in strategy by organization, not from the perspective of traditional financial proxy analyses, but by measuring dynamic positioning with a simple vector space model. We can assert that our methodology for measuring dynamic technology positioning yields methodological validity for two measurements as well as for practical implications.

Our method of analysis, using organizational relationships and technology management theory to process repurposed data, shows the effectiveness of the methodology. Revealed also is its potential for extracting significant knowledge with less processing and calculation through its use of the properties of huge amounts of existing data without vast amounts of professional indexing.

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