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Patent-based Measurements on Technological Convergence and Competitor Identification: The Case of Semiconductor Industry

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Abstract
Technological convergence promotes the formation and development of emerging industries associated with new opportunities and growth. It will be helpful for firms to understand the emerging trends of technology convergence and establish competitive strategy by identifying competitors. While previous studies mainly measure technological convergence with co-occurrence method on the technology level, relatively few studies investigate the measurement of technological convergence with firm-level data. In addition, how to identify competitors by firms in the background of technological convergence has been neglected by the extant studies. This paper takes the granted patent data of global top 10 semiconductor companies from 1994 to 2013 as the object and measures the degree and trend of technological convergence based on technology similarity. Furthermore the Multidimensional Scaling analysis with inter-firm technological similarity matrix is adopted to identify the competitors in the semiconductor industry. The main contribution of this research is that it proposes a novel method to measure technology convergence. The method is different from pervious literature in that it measures technology convergence and knowledge relatedness from a micro-level using patent data in semiconductor industry. In addition, the patent similarity matrix can be used as an input for competitor identification with Multidimensional Scaling analysis.
Keywords: Technological convergence; Competitor Identification; Multidimensional Scaling analysis; Semiconductor industry

1. Introduction

With the broadening range of science and technology and the deepening of cross-disciplinary research, technological convergence has emerged in many industries such as telecommunication, broadcasting, information technology, the food, the chemical, pharmaceutical, and entertainment industry (Kim & Kim, 2012). In general, convergence is used for the description that at least two discernable items gradually move towards a certain point or the items gradually change so as to become similar or develop something in common. In line with this view, technological convergence is defined as the process by which two hitherto different industrial sectors come to share a common knowledge and technological base (Athreye & Keeble, 2000). As a new mode of innovation, technological convergence not only promotes the formation and development of emerging industries, but also speeds up technological maturity and shortens the life cycle of technology (Kim et al. 2015).

Given the importance of technology convergence, a number of scholars have investigated the role of technology convergence in leading and dominating next-generation technological innovation (Athreye & Keeble 2000; Hacklin et al. 2009; Kim et al.2014). Lee et al.(2008) examined open innovation and its relationship with technological convergence in the mobile communication industry. Because of blurred industry boundaries, it is imperative for firms to establish diversified and cross-industry strategic partnership so as to adapt to the trend of technological convergence. Hacklin et al. (2009) found that innovation in the information communication technology industry is partly derived from the new applications with cross-disciplines. Therefore, technological convergence in essence is a type of innovation process. Taking the related registration patent of printed electronics technology from 1976 to 2012 as the case, Kim et al.(2014) identified the core technology in the process of technological convergence with social network analysis and investigated the dynamic evolution relationship between the core technology and component technology.

In recent years, some scholars began to pay attention to the measurement of technological convergence with methods such as co-occurrence analysis based on scientific literature and co-classification analysis based on patent data(Kim & Kim, 2012; Jeong et al.,2015; Gauch & Blind, 2015). Kim & Kim (2012) argued that patent citation can reflect knowledge flow in different technical fields and technological co-classification can measure the strength, speed and range of technological convergence, and thus proposed a measurement method of technological convergence based on patent data. By using patents filed to the Korean Intellectual Property Office (KIPO) from 1996 to 2010, Jeong et al.(2015) analyzed technological convergence in the Korean technology innovation system and its dynamic changes based on patent co-classification analysis. The results show that the diffusion of technological convergence has been ongoing since the early 2000s and technology convergence is evolving into a more complex and heterogeneous form. Gauch & Blind (2015) defined convergence as an inherently stable process of structuring inter-technological patterns over time and devised a set of methods to measure the level and trend of technological convergence, such as explorative identification of agglomerations of technical fields, the analyses of the breadth of technical fields to differentiate between focused and diffused convergence trends and in-depth analysis using a revised version of the Cross-Impact Assessment method.

To sum up, the existing literature mainly employs the co-occurrence analysis to measure technological convergence on technological level, which focuses on providing policy suggestions for government to promote technological convergence from the macro perspective. In spite of the contributions by previous literature, there are some limitations. First, most studies use concept frameworks and case study to analyze the mechanism of the convergence. A quantitative approach or empirical analysis of the convergence will add great value to the existing literature. Second, previous studies generally investigate convergence from a macro-level, micro-level analysis using firm-level data can be complementary to the existing literature. In addition, existing literature rarely explored the technological convergence on the firm level and competitor identification in the background of technological convergence has been neglected in previous literature.

This paper takes the global semiconductor industry as the research background and measures the technological convergence among firms with technology similarity proposed by Jaffe(1986), including static and dynamic analysis on technological convergence. Based on the similarity matrix, we use Multidimensional Scaling analysis to identify competitors in the semiconductor industry. The main contribution of this research is that it proposes a novel method to measure technology convergence. The method is different from pervious literature in that it measures technology convergence and knowledge relatedness from a micro-level using patents data in semiconductor industry. In addition, the paten similarity matrix can be used as an input for competitor identification with Multidimensional Scaling analysis.

2. Patent-based measurement on technological convergence

In general, convergence describes the concept of at least two discernable items moving towards union or uniformity or the merging of distinct technologies, devices, or industries into a unified whole(Curran & Leker ,2011) . According to this definition, convergence can be classified into different levels: science, technology, market and industry (Curran & Leker 2011; Jeong et al. 2015). Hacklin et al.(2009) and Curran & Leker (2011) found that technological convergence on different levels is not happening at the same time but occurs as a sequential process. Kim et al. (2015) further compared different patterns of technological convergence with inter-industries and intra-industries with co-occurrence method on newspapers and periodical articles. Athreye & Keeble (2000) argued that technological convergence is defined as the process by which two hitherto different industrial sectors come to share a common knowledge and technological base.

In this paper, we mainly investigated the technological convergence on the firm level. An industry is composed of a large number of companies which are endowed with different technologies and knowledge base (Curran & Leker 2011). In line with Athreye & Keeble (2000), technological convergence on the firm level can be defined as the process by which two hitherto different firms come to share a common knowledge and technological base. Therefore, technological convergence on the firm level can be measured by using the similarity of technological knowledge among firms in the industry. As the patents in different fields applied by firms are usually used to describe technological knowledge base. We use the patent vector in the technological space to describe technological position of different firms. For example, Jaffe(1986) describes technological position of firms with the distribution of patents in different patent categories. It is obvious that firms with the same International Patent Classification (IPC) are similar in some aspects of characteristics of technological knowledge base.

In previous literature, the patent data can be used to measure a firm's technological knowledge base. In this article, we assume that the technological knowledge base in each firm can be represented by a technological vector, and the number of granted patent indicates the technological knowledge accumulation in firms in the specific technology category. According to the International Patent Classificaation(IPC), we can distinguish the technological category and technological development direction for different firms. For example, firm *i*'s technological knowledge base can be expressed as: $f_i=(f_{1i}, f_{2i}, \ldots, f_{ni})$, where $1,2,\ldots,n$ represent different categories of technological patent according to IPC classification. f_{ki} (k=1, 2, …, n) represents firm i's number of the k'th granted patent. If firm i does not have the k'th technology, the number of the patents obtained by firm i in the k'th patent category is labeled as "0", i.e., f_{ki}=0. In this paper, we take the "class" of the IPC as the classification criteria for firm's patent. The s retrieval patent data shows that the granted patents in world's top 10 semiconductor firms involve 137 classes, which indicates that the vector includes 137 components. If the technological vectors of m firms can be seen as m points in n-dimensional inner product space, the technological convergence between firm i and firm j can be expressed as:

$$\text{TechCon}_{ij}=\frac{f_i f_j^{'}}{\sqrt{(f_i f_i^{'})(f_j f_j^{'})}} \quad \text{……………………………………}(1)$$

Where, vector $f_i^{'}$ and $f_j^{'}$ are the transpose vector of the vector f_i and f_j respectively.

If TechCon$_{ij}$=0, the technologies between firm i and firm j do not converge at all; if TechCon$_{ij}$=1, the technologies between firm i and firm j converge perfectly; and if 0<TechCon$_{ij}$<1, the technologies between firm i and firm j converge partly and the greater the value of TechCon$_{ij}$ indicates the higher degree of technological convergence between firms.

In order to analyze the trend of technological convergence in the semiconductor industry, we calculate pairwise the technological convergence of top 10 semiconductor enterprises each year with formula (1) and take the average value as the degree of technological convergence of the specific year in the semiconductor industry.

$$\text{D}=\frac{\sum_{l=1}^{C_m^2} TechCon_l}{C_m^2} \quad \text{…………………………………………………}（2）$$

Where, the TechCon$_l$ is the degree of technological convergence of a specific year between any two firms, m is the number of firms in the industry.

3. Research background and data sources

3.1 Research background

Although technological convergence has become a common phenomenon in many industries, the most significant technological convergence is still concentrated in the high-tech industries, such as information technology (IT), biotechnology (BT) and nanotechnology (NT) industry. As one of the high-tech industries, semiconductor industry not only ranks in the forefront of the most intensive R&D activities in most industries, but also provides the support of technology and intermediate product for other high-tech industries, such as computer equipments and telecommunications equipments. Therefore, the semiconductor industry which is related to IT and NT is selected as the research background. According to the ranks of global semiconductor manufacturers by Dataquest and IC Insights, we choose 10 firms which ranked stablely from 1994 to 2013 as the sample, including: Sony, Intel, Samsung, Toshiba, Qualcomm, Micron Technology, Broadcom, STMicroelectronics, Texas Instruments, and SK Hynix.

3.2 Data sources

Patent data and scientific literature have been the main data sources on technological convergence in previous literature. Compared with scientific literature, patent data reflect more directly the technological knowledge base of firms. Besides, patent data with time series can also be used to analyze the dynamic development of technology. Therefore, we use the patent data to analyze the technological convergence among firms in the semiconductor industry. Data retrieval strategies are as follows: taking the patent data retrieval system of Intellectual Property Office of the people's Republic of China as the search platform, with the name of the 10 semiconductors as the filing applicant and the "the United State" as the data searching range. We retrieve the patents of each firm from 1994 to 2013 based on the granted patent announcement date. For the patent data, we count respectively the number of retrieved patents of each firm based on the IPC's "class" as the criteria and form a series of patent vector.

4. Competitor identification based on technological convergence

4.1 Technological convergence within semiconductor industry

According to formula (1) and (2), we can calculate the degree of technological convergence of the global semiconductor industry in 1994~2013 and analyze the trend of technological convergence (See Figure 1).

As we can see from the Figure 1, the degree of technological convergence in semiconductor industry in 1994~2013 generally falls between 0.6 and 0.8, and shows a higher degree of technological convergence. Periodically, the degree of the technological convergence of semiconductor industry from 1994 to 2001 falls between 0.6 and 0.7, while from 2002 to 2013 falls between 0.7 and 0.8. Therefore, the degree of technological convergence of semiconductor industry in the past 20years generally shows an upward trend.

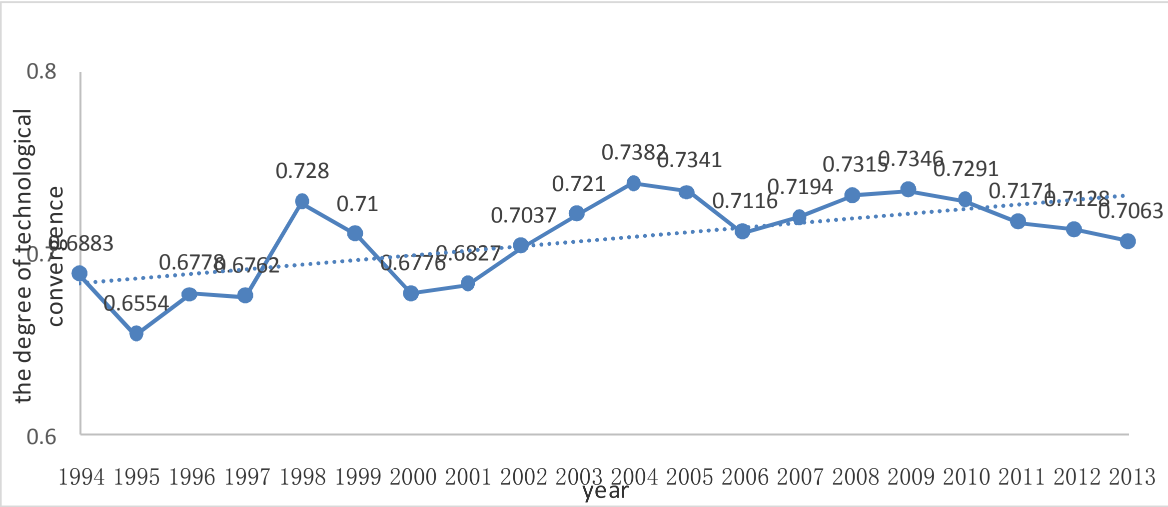

Figure 1 Trend of technological convergence in the semiconductor industry (1994~2013)

4.2 Competitor identification based on technological convergence matrix

Competitor identification is one of the important research topics in the field of competitive intelligence. Based on the measurement of technological convergence among the semiconductor firms, we construct the similarity matrix between the firms and employ the multidimensional scaling(MDS) analysis to identify competitors in the semiconductor industry. By using similarity matrix between firms, we generate a perceptual graph with multidimensional scaling analysis in which the degree of similarity among the firms is shown by the distance between points in the space. Higher similarity between firms will assemble together to form a category, and the more close to the center, the more central the status of the firm will be. Due to the lack of data in 1994~1999, we analyze the technological similarity matrix in 2000~2013 with MDS. Figure2~Figure7 are the 6 representative perceptual graphs.

Figure2~Figure7 show the competitors of the particular firms. In the graph, the closer the position between firms, the higher degree of technological convergence. That is to say, the more similar the technological knowledge base of firms, the more intense competition among these firms. From 1994 to 2012, Samsung, Sony and Toshiba, the top 10 diversified firms in the semiconductor industry, who are located in the center of the perceptual graph, which means that the competition among these three firms is intense for a long time. In fact, there are the fierce product and market competition among the Samsung, Sony and Toshiba in business area such as the video and audio equipment, optical disk storage, electronic component, computer and peripheral equipment and other products based on the semiconductor technological knowledge base.

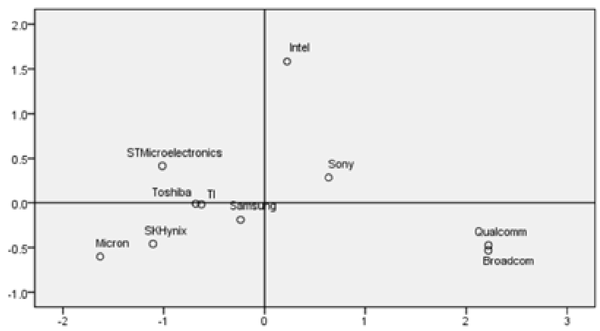

Figure 2 Perceptual graph for 2001

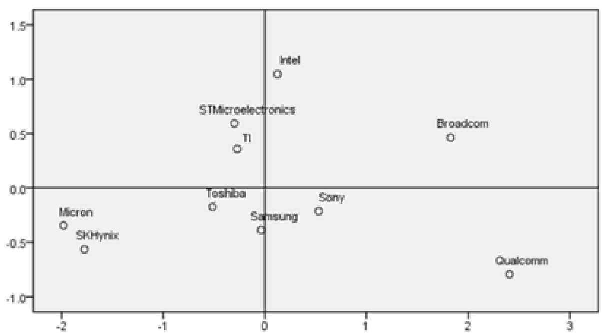

Figure 3 Perceptual graph for 2003

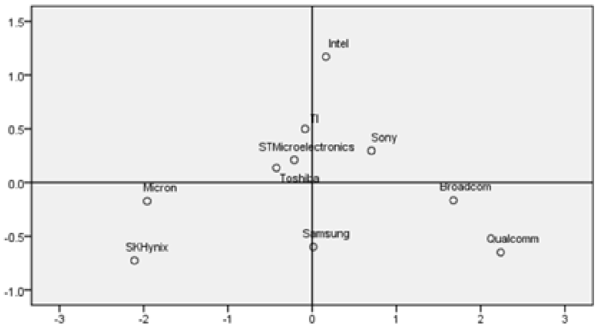

Figure 4 Perceptual graph for 2006

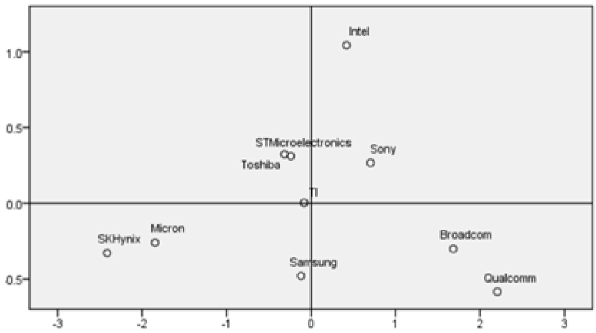

Figure 5 Perceptual graph for 2008

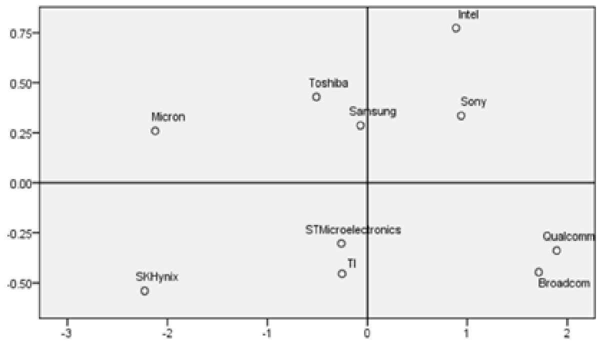

Figure 6 Perceptual graph for 2011

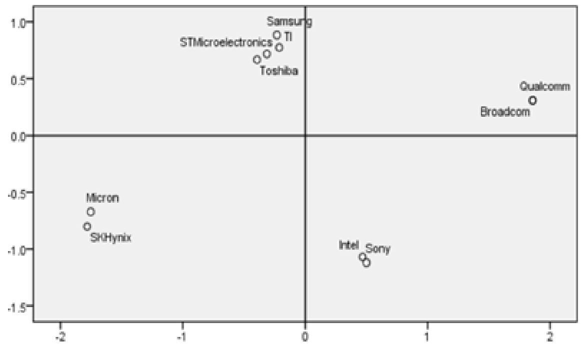

Figure 7 Perceptual graph for 2013

As indicated in these graphs, the positions of TI and STMicroelectronics in the perceptual graphs are closer and basically remain stable over time. According to the IPC the patent classification number of these two firms have been concentrated in H1~H5, G1~G11 and B1~B82(except B11~B20, B33~B40, B45~B59 and B68~B80). In addition, the number of patents with the same classification is basically comparable to each other, while the distributions of other patent classes are also similar. Therefore, TI and STMicroelectronics are the closest competitors to each other for a long time.

At the same time, based on the dynamic change in the perceptual graphs from Figure2 to Figure7, we can see that the distance of Broadcom and Qualcomm in the perceptual graphs was approaching since 2006 and the location of the two enterprises almost overlap by 2013. The IPC code of the two firms have been concentrated in H1~H5, G1~G11 before 2006 and since 2006 some patent classification numbers gradually appeared, such as B05, B23, B32, B44, B60, B81, F01, F02, F21, A61 and A63 with the similar distribution patterns. Meanwhile, compared with Qualcomm in the early years, the number of patents by Broadcom is less on the same classification code. However, the number of the patents by two firms on the same patent classification code is gradually increasing and the gap is decreasing over time. That is to say, the similarity of technological knowledge base (mainly in the area of integrated circuit design) between Broadcom and Qualcomm is increasing, and regional proximity between them further leads to the increasingly fierce competition.

In addition, the positions of SK Hynix and Micron Technology in the perceptual graphs are relatively close in almost every year. According to the distribution of IPC classification code, the two firms have been concentrated in H1~H5, G1~G11, while the numbers of the patent on the same classification code vary greatly. Apart from this, Micron Technology involves the classifications code such as B05, B08, B23~B25, B32, B44, B82, C01~C04, C07~C09, C11, C12, C23, C25, C30, A44, A47 and A61 while SK Hynix almost have no other patent distributions of classification number, but the two enterprises still maintain a longstanding competitive relationship.

In the perceptual graphs, the positions of Intel are relatively isolated (except in 2013). According to IPC code, the patents of Intel have been concentrated in H1~H5, G1~G11, B05, B32, C12 and F25. Having a large number of essential patents in the field of integrated circuit design(including the processors, memory and bus interface), Intel has launched many technological standards and established the image of “industry standard setter”, which laid the solid foundation for Intel’s competitive advantage in the semiconductor industry.

5. Conclusion

Since Rosenberg’s (1963) seminal work which found the phenomenon of technological convergence in the study of early evolution of the machine tool industry in the United States, technological convergence have promoted the formation and development of emerging industries through technology complement and cooperation as a new pattern of innovation and achieved the technological substitution in the market by a nonlinear way. Hence, innovation does not anymore take place within previously existing firms, but rather between them (Hacklin, Marxt & Fahrni, 2009).

Previous literature on technological convergence had focused on providing policies and recommendations for the government to promote technological convergence based on the macro perspective. For example, National Natural Science Foundation of the United States showed great interest in nanotechnology, biotechnology, information technology and cognitive technology(NBIC) and had been implemented the plan of the follow-up study since 2000(Wolbring 2008). Different from the existing literature, this paper take the micro perspective and analyzes the technological convergence on the firm level and then proposes a new method of competitor identification with the multidimensional scaling analysis. Specifically, as the industry is composed of a large number of firms endowed with different technological knowledge base(Curran and Leker 2011), the degree of technological convergence within the industry can be reflected by the similarity of technological knowledge bases among firms. Based on the granted patent data of the world's top 10 semiconductor companies in 1994~2013, we analyze the technological convergence and provide a new method of competitor identification with multidimensional scaling analysis. The results show that the degrees of technological convergence of the world's top 10 semiconductor companies are relatively high and show a gradual upward trend. In addition, using the similarity matrix of technological convergence among the semiconductor firms we can further identify the competitors in the semiconductor industry with the method of multidimensional scaling analysis.

6. Limitations and directions for future research

Although this study extends the application of patent analysis to measure the technological convergence and provide a new method for competitor identification, there are still some limitations. First, although patent data has been widely accepted as a proxy for technological innovation and has been used for technological convergence, there is no guarantee that technological convergence can be fully explained by the patent database. Future research should include other data sources (e.g. scientific literature database) to the analysis on technological convergence. Second, although the paper provides the measure for technological convergence, deep investigation on the antecedents and consequences of technological convergence are still needed in future research. Third, this paper examines technological convergence in the background of semiconductor industry characterized by intensive R&D activities and considerable amounts of patents, future studies should explore technological convergence in the context of medium- low - tech industries, which are neglected by most extant literature.

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