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Full Length Research Paper

Technological spillovers of transferred inventors from the perspective of Social Network Analysis (SNA)

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Personnel involved in high-tech R&D commonly move between enterprises, bringing with them technology obtained elsewhere. This leads to an imperceptible circulation of analogous technology among different companies. Unfortunately, this so-called technological spillover is difficult to detect. This study combined social network analysis with patent data covering nearly 30 years to construct the networks that involve the mobility of inventors and technological overlap in the Hsinchu semiconductor industry. Regression analysis using quadratic assignment procedures reveals that the network within which inventors migrate has a positive impact on the network technological overlap. Further analysis clarified the positive relationship between the mobility of inventors and technological overlap in terms of the organizational network characteristics. This confirms a process of co-evolution between technological overlap and the mobility of inventors, which may have a highly likely spillover.

Key words: Technological spillover, transferred inventor, social network analysis, technological overlap.

INTRODUCTION

Previous studies have emphasized the importance of innovation (Grant, 1991; Drucker, 1985; Schumpeter, 1934), revealing that more than one third of sales and profits in most industries are the result of recent developments. Schilling (2008) noted that the products developed by 3M in the previous five years contributed to 45% of total sales. Bhide (1994) pointed out that 71% of innovations in the 500 fastest growing companies in the United States involved the application or adaptation of previously acquired technical experience of newly transferred personnel. This phenomenon highlights the essential nature of personnel in innovation.

In competitive high-tech industries, personnel are often headhunted by other enterprises, and the philosophy of survival in Silicon Valley is, “If you have trouble with the competition, simply raid its talent (Kerstetter, 2000).” Individuals are the carriers of knowledge, and the flow of personnel inevitably leads to the transfer of technologies and methods between companies (Almeida and Kogut, 1999; Cantner and Graf, 2006) to enhance the career prospects of the individual involved (Cooper, 2001; Gorg and Strobl, 2005). This inevitably leads to the development of similar technology in both companies, resulting in frequent lawsuits related to patent infringement. In 2007, Foxconn filed a lawsuit against BYD for recruiting a high-level R&D director, who brought with him technology patented by Foxconn. In 2009, MediaTek sued ex-employees at MStar Semiconductor for their continued use of specialized software and data developed by MediaTek.

Previous studies have focused on the influence of geography and other factors on technological spillover (Krugman, 1991; Jaffe et al., 1993; Perez, 1997; Almeida and Kogut, 1999; Piergiovanni and Santarelli, 2001; Maurseth and Verspagen, 2002; Stolpe, 2002; Kim and

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Marschke, 2005; Thompson, 2006). However, various factors were neglected in these studies, such as transferred personnel and their extended personal relationships, which often have a greater impact than spatial limitations (Agrawal et al., 2003; Breschi and Lissoni, 2003). Although economists have long suspected that the movement of scientists between enterprises enhances the transfer of technology and knowledge (Arrow, 1962; Stephan, 1996), the channels associated with technological spillover remained unidentified (Gorg and Strobl, 2005), and a lack of empirical evidence, increased the difficulty of measuring the effects.

Jaffe et al. (1993) pointed out that although knowledge spillover was invisible, it left long trails through patent documents, in the form of citations. Most studies on technological spillover have employed patent citations in their analysis. This study assumed that if the mobility of personnel induces technological spillover, it must also leave a similar paper trail. For example, it has been revealed that the patents of an individual inventor are held by a number of different companies (mostly due to job change, or inter-firm's joint invention), and the technological categories of these patents are usually the same. This indicates that the inventor probably leaked technologies. In addition, Cantner and Graf (2006) constructed three organizational networks representing the relationships between past cooperation, the mobility of scientists, and technological overlap in Jena, Germany. Although the main purpose was to verify the influences of the latter two on the first, their research provided the means with which to reconstruct the circumstances leading to particular events. This study applies the aforementioned concepts to develop a research framework linking technological spillover and the mobility of inventors in patent documents.

Over half of the semiconductor industry of Taiwan is located in the Hsinchu Science Park and surrounding areas, forming a complete cluster of related industries. Previous studies have already concluded that clustering has a positive influence on productivity and innovation (Maurseth and Verspagen, 2002; Waguespack and Birnir, 2005); the proximity of clustered enterprises facilitates the sharing of information thereby increasing the likelihood of technological spillover (Jaffe et al., 1993; Tsai, 2005). Since the establishment of the first company in 1979, the Hsinchu industrial cluster has accumulated a substantial number of patents at the United States Patent and Trademark Office (USPTO). Therefore, these patents meet the requirements of this study.

Technological spillover resulting from the mobility of the patent inventors always causes companies to lose R&D resources, blurring the distinctions between technologies found in different companies. For this reason, this study used patent data and Social Network Analysis (SNA) to reproduce the process by which inventors transfer between enterprises, the technological overlap this creates, and the consequences.

LITERATURE REVIEW

Technological spillover is a common phenomenon in industry (Bernstein and Nadiri, 1988). Cincera (1997) described the connotations of technological spillover as the "borrowing" of technological knowledge from one firm by another. Unlike the intentional transfer of knowledge, technological spillover is "unintentional" (Fallah and Ibrahim, 2004), and its progress is usually difficult to observe. Technological spillover is most commonly expressed through data related to patent citations (Weng and Lai, 2009; Jaffe, 1989; Jaffe et al., 1993; Jaffe and Trajtenberg, 1999; Almeida and Kogut, 1999; Rosenkopf and Nerkar, 2001; Stolpe, 2002; Maurseth and Verspagen, 2002; Breschi and Lissoni, 2003; Thompson, 2006), and in particular, back citations (Wartburg et al., 2005). However, a number of experts have claimed that the use of patent data is flawed because patents only reflect a limited number of the factors related to technological spillover, leaving other factors such as the imitation issue undisclosed (Nadiri, 1993). Some studies have utilized outcome variables to represent the existence of spillover, such as enterprise output value, the number of patents, and employee salaries. (Park, 1995; Coe and Helpman, 1995; Cincera, 1997; Piergiovanni and Santarelli, 2001; Møen, 2005; Gorg and Strobl, 2005) Regardless of whether patent citations or outcome variables are used, previous studies have seldom used technological overlap between enterprises as a measure of spillover. It is widely known that similarity in technology is a result of technological spillover (Wang and Blomstrom, 1992). Cantner and Graf (2006) used shared international patent classification (IPC) to represent technological overlap. Although they obtained a correlation coefficient of 0.352 between the networks formed by the job mobility of scientists (1995 to 1997) and the technological overlap (1995 to 1997), they did not seek to verify this positive relationship. A fraction of their research subjects were academic scientists and research institutes, for which spillover was common and obvious, because the academic community has a tradition of disclosing research results through publication. Studies have shown that even after controlling for related factors, the diffusion of knowledge in the academic community is still rapid (Sorenson and Singh, 2007).

In general, enterprises gain technology through channels such as licensing agreements, cooperative R&D, published patents, publications, conferences, field trips, social gatherings, reverse engineering, and direct recruitment of employees of other companies. The mobility of labor resulting from directly recruiting the employees of other companies has always been an important cause of technological spillover (Arrow, 1962; Saxenian, 1994; Rosenkopf and Almeida, 2003; Møen, 2005; Singh, 2005), and this method is very effective (Khalil, 2000). Almeida and Kogut (1999) defined personnel technological spillover as the outcome resulting from the mobility of skilled labor in certain spatial markets. This kind of spillover often gives rise to non-compete disputes following the termination of employ-ment. The personnel who contribute to technological spillover are usually engineers, scientists, or other knowledge workers (Audretsch, 1998). Employers may obtain unexpected externalities when they hire new recruits, or suffer a reduction in return from R&D investments after employees leave (Møen, 2005). However, such highly trained personnel, particularly those credited with important patents, are often found circulating between various enterprises, (Almeida and Kogut, 1996, 1999).

Previous studies on technological spillover, have focused primarily on the direction of technological spillover, such as, between nations, multinational enterprises, industries, and firms within industries (Jaffe, 1986; Bernstein and Nadiri, 1988; Basant and Fikkert, 1996; Bernstein and Yan, 1997; Jaffe and Trajtenberg, 1999; Madden et al., 2001; Zhu; 2007; Mercedes and Maudos, 2009), as well as the influential factors, such as geographical location, knowledge infrastructure, private R&D activities, technology gaps, learning and imitating abilities, and various methods and mechanisms related to intellectual property (Krugman, 1991; Jaffe et al., 1993; Perez, 1997; Almeida and Kogut, 1999; Piergiovanni and Santarelli, 2001; Maurseth and Verspagen, 2002; Stolpe, 2002; Kim and Marschke, 2005; Thompson, 2006). Among these issues, geographical factors have been mentioned most often, with studies addressing clusters, international or domestic issues, and regional matters. Jaffe et al. (1993) indicated that technological spillover is often a localized phenomenon; however, Agrawal et al. (2003) pointed out that the patents of inventors are still cited by co-inventors even after the inventor has already moved on. Breschi and Lissoni (2003) stated that geographical space is inadequate to explain the formation of knowledge in given areas, but claimed this could be explained by the mobility of personnel. One research report by the Organization for Economic Cooperation and Development (OECD) in 1997 showed that the relocation of technology personnel between the public and private sectors is one form of knowledge flow or technology flow. The aforementioned studies all reveal that the influence of personnel mobility and its relationship to technological spillover extends beyond geographical limitations. Nonetheless, the importance of this issue is often neglected, which may be the result of difficulties associated with compiling empirical evidence to support such a contention.

Personal networks do not collapse following a change of position or job[1].The newly recruited R&D personnel may even establish association channels between new and former colleagues, leading to technological spillover. Many studies, such as Zander and Kogut (1995), Zucker et al. (1998), and Sorenson (2004), have verified that relation-ship networks are related to the diffusion of technology. They have indicated that the spread of information or technology, in particular, tacit knowledge, which is difficult to encode, is often delivered through personal networks (Uzzi, 1996), and Berman et al. (2002) described the tacit knowledge as the knowledge embedded in social networks that spreads and flows. Singh (2005) again indicated that being in the same region or firm is found to have little additional effect on the probability of knowledge flow among inventors who already have close network ties. As to the industry, Almeida and Kogut (1999) asserted that the flow of knowledge was embed-ded in the regional labor network. Briefly, individuals with close interpersonal relationship do make the transmission of knowledge easier (Allen, 1977; Nonaka, 1994).

Networks promote learning, and can be regarded as the cumulative trajectories of knowledge generated previously (Dyer and Nobeoka, 2000; Podolny and Page, 1998). If the relationships associated with a social net-work are used to acquire or disseminate knowledge, then it is in fact a knowledge network (Hansen, 2002). Studies on the semiconductor industry in Taiwan have discovered that, in addition to bringing back new technology and concepts, the tide of talent returning to Taiwan between 1985 and 1992 to start enterprises also maintained ties with colleagues in their overseas place of residence, thereby promoting the development of the semiconductor industry in Taiwan (Saxenian, 2002).

Whether certain features of a network structure affect the diffusion of technology between nodes has also always been an important research topic. Powell et al. (1996) discovered that the degree of centrality in a network determines the rate of learning within an organi-zation. Inkpen and Tsang (2005) indicated that social capital plays an important role in the transfer and ex-change of knowledge. Gautam's (2000) study addressed firms in the chemical industry, revealing that the ties of a network (both direct and indirect) have a positive impact on innovation, as represented by the number of patents, and structural holes are proposed to have both positive and negative influences on subsequent innovation.

In summary, the individuals migrating between firms and their extended personal relationships play a key role in technological spillover, which can no longer be overlooked.

RESEARCH METHODS

Framework

This study proposes that the transferred inventors who have worked for different firms (that is, patent assignees) influence technological spillover, resulting in the development of similar tech-nology in different firms. This phenomenon of transferred inventors can be observed through an analysis of documents pertaining to

[1] Field investigations performed by Fleming et al. (2003, 2004) discovered that the co-inventors listed on patents more or less have personal or professional relationships

Table 1. Example of patent database.

Application date	Patent number	Inventor	Assignee	International patent classification	United States patent classification
D1	PN1	IN1, IN2	AS1, AS3	IPC1, IPC3	UPC1
D2	PN2	IN3	AS1	IPC2	UPC2, UPC4
D3	PN3	IN3, IN4	AS2	IPC2	UPC2
D4	PN4	IN5	AS3	IPC3, IPC4	UPC3
D5	PN5	IN5	AS3	IPC5	UPC4
D6	PN6	IN6, IN7	AS3	IPC6	UPC1, UPC2
D7	PN7	IN1	AS4	IPC1	UPC1
D8	PN8	IN4	AS4	IPC3	UPC3
D9	PN9	IN8	AS4	IPC2	UPC2

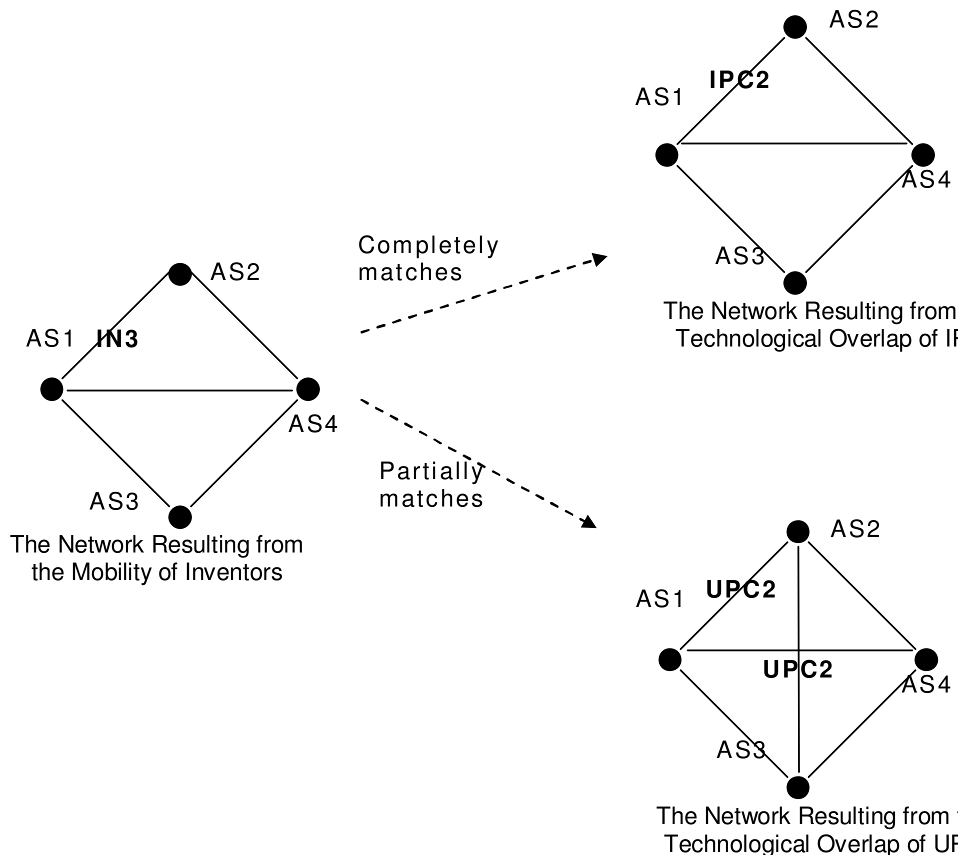

Figure 1. Example of firm networks and match.

past patents. If different assignees chronologically appear in an inventor's all patents, it indicates that the inventor has shifted. This situation is defined as the mobility of inventors between firms. A link, or line, can be drawn between the initial and subsequent firms for the reconstruction of the event. These links represent the developmental trajectory of the event. Using the patent data in Table 1 and the lines in Figure 1 as an example, IN3 is the connection with the inventor moving between assignees AS1 and AS2. Correspondingly, the technological similarity between firms can also be determined from past patents. Different assignees having the same technological classification codes in patents indicate that their technology is similar and related, and we refer to this situation as technological overlap between firms. The classification codes IPC2 and UPC2 attached to the patents PN2 and PN3, represent the shared or overlapped codes between the assignees AS1 and AS2, which can also be illustrated by a line between two firms. According to the temporal sequence in Table 1, we can see that IPC2 and UPC2 were transferred or spilt from AS1 to AS2 by IN3. Therefore, the line of the transferred inventor precisely matches the line of the overlapped codes. All links concerning the mobility of inventors and the technological overlap between firms in Table 1 are presented in Figure 1 as three net-like combinations: networks resulting from the

Table 2. Example of the mobility of inventors incidence matrix in firms.

Variable	IN1	IN2	IN3	IN4	IN5	IN6	IN7	IN8
AS1	1	1	1	0	0	0	0	0
AS2	0	0	1	1	0	0	0	0
AS3	1	1	0	0	1	1	1	0
AS4	1	0	0	1	0	0	0	1

Table 3. Example of IPC technological overlap incidence matrix in firms.

Variable	IPC1	IPC2	IPC3	IPC4	IPC5	IPC6
AS1	1	1	1	0	0	0
AS2	0	1	0	0	0	0
AS3	1	0	1	1	1	1
AS4	1	1	1	0	0	0

Table 4. Example of UPC technological overlap incidence matrix in firms.

Variable	UPC1	UPC2	UPC3	UPC4
AS1	1	1	0	1
AS2	0	1	0	0
AS3	1	1	1	1
AS4	1	1	1	0

from the mobility of inventors, the
technological overlap of IPC, and the technological overlap of UPC (here referred to as IM network, TOI network and TOU network).

Comparing any pair of IM and technological overlap networks allows for the interpretation of spillover from the mobility of inventors. As shown in Figure 1, the structure of IM and TOI networks match precisely, revealing that the technological overlap in IPC in IPC between the firms was caused entirely by the mobility of inventors. In the structure of IM and TOU networks, UPC2 lines between AS2 and AS3 did not match, and therefore it was determined that the shared UPC2 was not spilt by the transferred inventors, indicating that the overlap of technology in UPC between the firms was only partially due to the mobility of inventors. A wide range of factors contributes to technological overlap between firms, and the mobility of inventors is only one of them. For this reason, IM network and technological overlap networks only partially match. The reconstruction and comparison of large numbers of lines associated with the mobility of inventors and technological overlap can be achieved by the SNA.

Degree of the mobility of inventors and technological overlap

The SNA only displays lines between firms, and the degree of mobility of inventors and technological overlap of a firm must be expressed by calculating the *inventor-mobility rate* and the *technological overlap rate* derived from patent data. The method is as follows: Tables 2, 3, and 4, called incidence matrices, can be generated from Table 1. The total number of rows in the incidence matrices equals the total number of inventors or technological classification codes for each firm. The number of inventors that have transferred or the overlapped technological classification codes can be counted from each column. The two rates for each firm are calculated by dividing the column total by the row total. In Table 2, the AS1 row shows that firm AS1 has a total of three inventors, and from the columns of those three inventors, it can be seen that all three have worked for other firms; therefore, the mobility rate is 3/3 = 1. Similarly, the mobility rates for AS2, AS3, and AS4 are 1, 0.4, and 0.67, respectively. In Table 3, the rate of IPC technological overlap of the four firms is 1, 1, 0.4, and 1, and in Table 4, the rate of UPC technological overlap of the four firms are 1, 1, 1, and 1.

Data

Patents are documents of technological achievements as well as data commonly used for technological research (Ernst, 2003). To confirm the influence of the mobility of inventors on technology overspill, patents are even more necessary. This study acquired patent data from the USPTO database via the PatentGuider 2.0. The list of firms in the Hsinchu semiconductor industry cluster was obtained from: (1) the newest annual edition of Overview on Taiwan IC Industry, published by the Taiwan Semiconductor Industry Association (TSIA), and (2) the firm registry of the Association of Industries in Science Parks (ASIP) website. This included 147 firms and academic research institutes, 98 of which were situated in the Hsinchu Science Park, and 49 in surrounding areas. Five firms were equipment related; 102 were IC design firms; 15 were IC manufacturing firms; 5 were packaging firms; 4 were testing firms; 8 were opto-semiconductor manufacturers; and the last 8 were academic research institutes[2].

Academic research institutes are of critical importance to industry clusters (Monck et al., 1988; Massey et al., 1992; Westhead and Batstone, 1998; Piergiovanni and Santarelli, 2001), representing a

[2] One was the Taiwan Industrial Technology Research Institute (ITRI), and the other seven belonged to various universities.

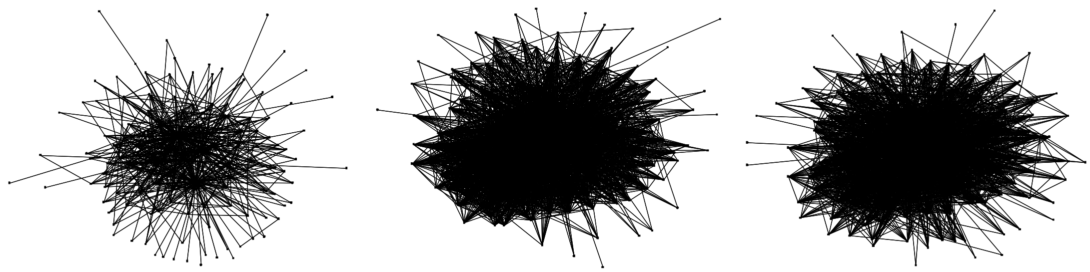

Figure 2. The networks resulting from the mobility of inventors (left),technological overlap of IPC (middle) and UPC (right) in Hsinchu, 1980 to 2009.

supply of technical labor, providing the fringe benefit of skill in R&D (Breznitz, 2005), which is the reason this study included their patents in the data collection. The collected data covered the time period of December 15, 1980, which is the establishment date of Hsinchu Science Park, to December 15, 2009. The keywords used for the search were the English names of firms registered in Taiwan. A total of 18,006 patents were obtained from the search, among which there were 11,762 inventors, 7,953 IPC and 14,108 UPC codes respectively[3].

RESULTS

Descriptive statistics

Networks resulting from the mobility of inventors and technological overlap in the semiconductor industry are shown in Figure 2[4]. In the initial comparison, the IM network and both technological overlap networks were contained in scale, indicating that the transferred inventor lines between nodes (In addition to companies, the study also includes academic and research institutions. We use a more neutral terminology from SNA, "node", to represent all research objects here and onwards) may partially match the overlapped code lines; the mobility of inventors could partially explain the reason for technological overlap. The appearances of the two technological overlap networks are quite compatible and imply that the classification results of both IPC and UPC systems are probably the same.

Most of the statistics of the network in Table 5 are commonly used in SNA. These statistics concern two levels: the whole network and the individual nodes. Rows (01) through (07) belong to the former, and the remainders belong to the latter. In terms of (02), the number of isolated nodes (node without any link) in the IM network is higher than those in the TOI and TOU networks. This is most likely related to the fact that the nodes are all positioned in the same industry, and the classifications of the technologies were easily overlapped; however, the professional specialty of the inventors in these isolated nodes may be more specific, as it is not easy to transfer to other nodes.

The density values (03) of each network are low, revealing that there is little direct contact between any two nodes. This also corresponds to the low mean nodal degree (14). The nodal degree is the number of nodes that are directly linked through the transferred inventors or overlapped technological classification codes, and the density of the network associated with the degree. However, densities of certain business types in the technological overlap networks are very high; the densities of the IC manufacturing firms in the TOI and TOU networks were 0.99 and 0.97, respectively, indicating a homogeneity of skills. In addition, most firms were involved in IC design, but their IM network density was only 0.03. The exchange of inventors between firms in the patents of IC design was infrequent.

According to social network theory, the degree centralization value is 1 for a star network and 0 for a loop or circle network. The three semiconductor industry networks (04) all had values of roughly 0.6, indicating that the networks did not lean towards either extreme. Row (14) shows the mean degree of a node, and is lower in the IM network but higher in the technological overlap networks. The high degrees nodes were primarily the Taiwan Industrial Technology Research Institute (ITRI) and IC manufacturing firms, indicating that many organizations have a direct interaction with them through exchange of inventors or technological classification codes.

In Table 5, row (5) shows that all three networks have high connectedness values. Rows (15) and (16) indicate that the node has a short mean distance and a high mean connectivity[5], respectively. The clustering coefficient (06) is one of the indices commonly used to the

[3] After checking the name data, those that were possibly the same person but spelled differently due to different phonetic spelling systems were corrected. Before correction, there were 14,441 names in which 2,679 were corrected. The correction rate was 19%. Unlike previous studies using simplified technological classification data, for example, classification data of one higher level, the technological classification codes applied in this research are in full accordance with the patent documents without any treatment, so as to be more effective in presenting the complete facts to be explored.

[4] The network figures as well as the following analysis were all processed by Ucinet 6.232.

[5] If there are n nodes in a network, then each node has an n-1 connectivity value. Therefore, this study selected the mean value to represent the connectivity of each node.

Table 5. Descriptive statistics of all networks.

Statistic	IM Network	TOI Network	TOU Network
(01) Number of nodes	147	147	147
(02) Number of isolates	25	1	2
(03) Density	0.06	0.28	0.25
(04) Degree centralization	0.56	0.66	0.67
(05) Connectedness	0.69	0.99	0.97
(06) Unweighted/weighted clustering coefficient	0.78/0.30	0.82/0.57	0.81/0.52
(07) Betweenness centralization	0.22	0.13	0.11
(08) Mean/max number of inventors	95.2/3684	-	-
(09) Mean/max number of transferred Inventors	28.17/735	-	-
(10) Mean/max inventor-mobility rate	0.42/1	-	-
(11) Mean/max number of technological classification codes	-	110.37/4538	216.05/6918
(12) Mean/max number of technological overlap codes	-	73.18/1376	157.37/3114
(13) Mean/max technological overlap rate	-	0.89/1	0.86/1
(14) Mean/max degree	8.97/90	40.35/135	36.29/133
(15) Mean/max distance	2.11/4	1.74/4	1.77/3
(16) Mean/max connectivity	2.98/8	22.19/39.38	19.39/35.28
(17) Mean/max constraint	0.29/1	0.13/1	0.12/1
(18) Mean/max betweenness	55.67/2350	53.6/1421	54.36/1172
(19) Mean/max line betweenness	1.45/33.02	1.72/20.46	1.72/17.04

the controllability of a whole network with respect to the interaction between nonadjacent nodes. In a star network and a loop network, the values are equal to 1 and 0, respectively. Row (07) shows that the values of the betweenness centralization of the three networks, are not significant high. In (17) and (18), the mean betweenness (representing the average controllability of a single node with respect to the interaction between nonadjacent nodes), and the constraint (which conversely measures the average nodal level of control by other nodes) in the networks are also not significantly high. This result may be due to the high connectivity in the earlier mentioned; each node has other nodes to contact without needing to go through the intermediate, or "middle", nodes. In (19), the line betweenness[6] is the reverse and represents the mean controllability of the nodal transferred inventors or overlapped technological classification codes in the interaction between nodes. It also expresses the probable importance of the nodal transferred inventors or overlapped codes. The mean values are also not significantly high, which may also be due to the high connectivity. Each node has other paths (lines) to bypass the intermediate lines and contact other nodes. ITRI had the highest betweenness of the three networks. As this organization is a government established research institute, its goal is personnel training and the transfer of technology, which may be the cause of the higher betweenness.

The statistics from (08) to (13) display a wide discrepancy. These values are associated with the transferred inventors and technological classification codes owned by a node. The nodes with the highest values were still primarily ITRI and the IC manufacturing firms. Rows (10) and (13) indicate that for the given node over average forty percent of the inventors had transferred before and over eighty percent of the technological classification codes overlapped with those in other nodes.

From the ongoing outline, we see that the three networks in the Hsinchu semiconductor industry cluster do not possess a high density, implying that these organizations seldom have direct contact but easily make indirect contact with others, due to high connectedness, and this also results in having less control over each other. Further, we examine whether the high degree of technological overlap is connected to the mobility of inventors.

Regressions of the networks

The figure earlier presented reveals that the scale of the IM network can be encompassed by two technological overlap networks. Whether or not there is a line match, that is, "whether the mobility of inventor relationships (IM network) can explain the technological overlap relationships (technological overlap network) between nodes" as

[6] If there are n nodes in a network, then each node has an n-1 line betweennesses value. Therefore, this study selected the mean value to represent the line betweenness of each node.

Table 6. Results of network regression.

Variable	TOI network	TOU network
IM Network	0.357**	0.371**
R^2	0.127**	0.138**
Adjusted R^2	0.127**	0.138**
TOI Network	-	0.721**
R^2	-	0.520**
Adjusted R^2	-	0.520**
TOU Network	0.721**	-
R^2	0.520**	-
Adjusted R^2	0.520**	-

†P<0.1, *P<0.05, **P<0.01.

described in social network theory must be answered by QAP (quadratic assignment procedure) regression (Krackhardt, 1987, 1988; Everett, 2002). The adjacency matrices of the TOI and TOU networks were the dependent variables; the adjacency matrix of the IM network was an independent variable; the results are shown in Table 6. The first section of the table shows that the regression coefficients between the IM network and the TOI and TOU networks are significantly positive. Although the adjusted R^2 values were only 0.127 and 0.138, they were highly significant. The mobility of inventors between the nodes effectively explains the 12.7 and 13.8% variation in technological overlap, confirming the opinion that the mobility of inventors partially influences technological overlap. The results above also disclose the possibility of technological spillover from the transferred inventors.

The second and third part use the two technological overlap networks as reciprocal dependent or independent variables. The results reveal that the TOI and TOU networks possess a significantly positive correlation of 0.721. This explains the 52% variance between them, confirms an incomplete match between both networks, and indicates that both classification systems produce mostly the same classification results, but still have some differences. Therefore, in the following analysis, it is necessary to conduct the analysis in two directions: on the TOI network and on the TOU network.

Regressions of the nodal network characteristics

The regressions of the whole network confirmed the positive relationship between the mobility of inventors and the technological overlap. We then used the network characteristics of the nodes (Table 5) to further explore how the mobility of inventors had influenced the technological overlap in the Hsinchu semiconductor cluster. The nodal characteristics in the IM network were independent variables, and those in the TOI and TOU networks were dependent variables. This was all still determined using QAP regression. The results are shown in Tables 7 and 8. Most of the coefficients of the primary, i.e. the diagonal, are significantly positive. The detailed description is as follows:

To begin, the first groups (columns) of regressions in the two tables have significantly positive coefficients between nodal inventor-mobility rate and technological overlap rate. This result indicates that the nodal degree of mobility of inventors is proportional to the degree of technological overlap. This is a reconfirmation of the result and clarifies the findings so far. Moreover, the nodal degree in the IM network has an impact on their technological overlap rate only in the TOI network. The adjusted R^2 in the first group regression, must be 10%, to be significant in Table 7, but did not reach any desired level of significance in Table 8.

Both second groups of regressions had high and significantly adjusted R^2 values, revealing in a consistent manner that the nodal degree and connectivity in the IM network are significant correlated with their degrees in the technological overlap networks. The coefficients of the former pair indicate that if a node has other direct inventor-exchange nodes, it will have other direct code-share nodes, that is, a higher level of inventor nodes exchange will allow more nodes to share codes. This appears to explain how technology spreads. The nodal connectivity represents how easily the node establishes contact with other nodes in a relationship network. In the latter pair, the high nodal connectivity of the transferred inventors can also increase the number of nodes to share codes with.

High and Significant adjusted R^2 values still remain in both the third groups of regressions revealing in a consistent manner, that the nodal connectivity in the IM and technological overlap networks have significantly positive coefficients. These findings indicate that the high nodal connectivity of the transferred inventors also

Table 7. Regressions of the nodal characteristics in IM and TOI networks.

Variable	Technological overlap rate	Degree	Connectivity	Constraint	Betweenness	Line betweenness
Inventor-mobility rate	0.250**	-0.228	-0.302	0.297**	-0.090	-0.090
Degree	0.419†	0.458†	-0.165	0.338	-0.228	-0.228
Connectivity	-0.456	0.782**	1.024†	-0.535	0.660*	0.660*
Constraint	-0.214	0.171	0.081	0.014	0.244†	0.244†
Betweenness	-2.753	2.263	1.215	1.230	4.327*	4.241*
Line betweenness	2.235	-2.458	-1.214	-1.365	-3.506	-1.429
R^2	0.177†	0.803**	0.597**	0.153†	0.848**	0.847*
Adjusted R^2	0.136†	0.793**	0.577**	0.111†	0.841**	0.840*

The variables listed in rows are the nodal characteristics in the IM network; while those listed in columns are the nodal characteristics in the TOI network. †P<0.1, *P<0.05, **P<0.01; all have 147 samples.

Table 8. Regressions of the nodal characteristics in IM and TOU networks.

Variable	Technological overlap rate	Degree	Connectivity	Constraint	Betweenness	Line betweenness
Inventor-mobility rate	0.170*	-0.256	-0.345	0.151†	-0.103	-0.111
Degree	0.249	0.703*	0.000	0.170	0.468†	0.453†
Connectivity	-0.170	0.487†	0.753*	-0.241	0.235	0.255
Constraint	-0.234	0.074	-0.075	0.268†	0.151	0.160
Betweenness	-1.365	0.162	-1.530	2.927	2.090	2.124
Line betweenness	1.005	-0.415	1.508	-3.025	-1.746	-1.777
R^2	0.093	0.814**	0.629**	0.153†	0.801**	0.801**
Adjusted R^2	0.048	0.805**	0.610**	0.111†	0.791**	0.791**

The variables listed in rows are the nodal characteristics in the IM network; while those listed in columns are the nodal characteristics in the TOU network. †P<0.1, *P<0.05, **P<0.01; all have 147 samples.

effectively facilitates code-overlapped connections with other nodes in this semiconductor cluster. This may be an inevitable result brought about by nodes concentrated in a small area, such as a cluster effect.

The dependent variables in the last three groups of regressions represent the controlled and controlling levels of the node or the line for the code-overlapped connections between nodes. The adjusted R^2 values in the fourth group of regressions had to reach the significance level of 10% to be significant. The nodal inventor-mobility rate and constraint in the IM network possess significantly positive coefficients with their constraint in the technological overlap networks. The coefficients of the former pair indicate that the greater the nodal mobility of inventors, the more easily the nodes are controlled during the code-overlapped connections with nonadjacent nodes. The node statistics shows that the ten nodes with the most patents possessed an average inventor-mobility rate of 0.33 with an average constraint of 0.04 in both technological overlap networks. The other 137 nodes possessed an average inventor-mobility rate of 0.43 with an average constraint of 0.14 and 0.13 in the TOI and TOU networks, respectively, which were nearly 3.5 times larger

larger than those of the top ten nodes. The number of possessed patents was related to the scale of the node. Nodes with more patents were usually larger and had a lower staff turnover, and therefore owned plenty of technological classification codes. In the construction of the technological overlap networks, the other nodes were easily code-overlapped with them so theoretically they had a high probability of obtaining the status of an intermediary in SNA. On the contrary, for the smaller nodes with fewer patents, codes and high mobility rate were easily controlled in the networks. As for the coefficient of the latter pair, the nodal constraint in the IM network has a significant impact on the nodal constraint only in the TOU network. This is exactly in contrast to the positive relationship between nodal connectivity to connectivity in the third group. The adjusted R^2 values of the fifth and sixth groups of regressions reached the desired level of significance. In the fifth group of regressions, the significant independent variables are the nodal connectivity, constraint, and betweenness in Table 7, and the degree in Table 8. Inconsistent results between the two tables also occurred in the sixth group of regressions. However, the differences between their adjusted R^2 values are very small so that no one is representative. Earlier, we found the probable classification gap of patents between the IPC and UPC, this relationship seems to be reflected here.

The findings here show an important feature: the same nodal characteristics separately belong to IM and technological overlap networks, and almost jointly possess a significantly positive relationship (Tables 7 and 8), apart from line betweenness. There is a tendency for a gradual co-development of the mobility of inventors and the technological overlap in Hsinchu semiconductor industry patents.

CONCLUSION AND DISCUSSION

Just as footprints in the sand show where one has been, technological spillover leave clues in patent documents (Jaffe et al., 1993). If past events can be recorded in a linear combination such as a network, then research about technology can be implemented via social network analysis. This study utilized inventors, assignees, and technological classification codes in patent documents to reconstruct the past mobility of inventors and technological overlap in the Hsinchu semiconductor industry. We then found that most organizations have few direct links but which easily establish indirect contact with others through transferred inventors and overlapped technological classification codes.

However, IC manufacturing with the highest production value in this cluster had intensive code-overlapped connections. This shows the homogeneity of technology within them. Moreover, not surprisingly, indirect contact through a wide range of relationships is facilitated in areas where many firms are concentrated. By QAP regression, we first confirmed that the mobility of inventors has a positive impact on the technological overlap among organizations. Next, we further clarified how the mobility of inventors has influenced the technological overlap by testing the network characteristics of the nodes. Most of the nodal network characteristics of the mobility of inventors had an influence on those of the technological overlap. This confirms a process of co-evolution between technological overlap and the mobility of inventors.This study provides another option for research investigating the factors of technological spillover: visualizing the progress trajectories and comparing them to speculate on the relationships therein. In addition to focusing on issues of technology management, this method could also be applied to the search and placement of professionally skilled human resources. A few other issues arising from this study are worthy of further discussion. First, in this study, technological spillover from the mobility of inventors is a highly probable phenomenon with a strong impact on the enterprises involved, requiring more circumspect laws and improved measures to protect them. Next, the degree of technological overlap within the Hsinchu semiconductor industry cluster is very high; implying a lack of unique technologies produces an effect similar to that found in biology, the founder effect, which can reduce the industry or national competitiveness. The production value of this cluster is too concentrated on IC manufacturing. However, upstream IC design, which is a high value added sector, still has room for improvement.

The reasons for, and consequences of, the high degree of technological overlap require additional research to be understand fully.

Consequently, although the mobility of inventors is responsible for part of the technological overlap between organizations, the types and importance of these “borrowed” technologies still need further consideration. Finally, the two technological classification systems may produce different results for the same patents, and this effect also deserves further attention. This study has a number of limitations. For example, the non-compete obligations following the termination of employment were not considered, as this would have influenced the degree to which technological overlap developed between the former and present enterprises in the years after an inventor changed jobs. Whether or not this obligation has been violated is the basis of many disputes between former and present employers.

However, there are no specific laws or regulations addressing this issue in Taiwan, and this tends to be purely an agreement between employee and employer. The time limits in each agreement are different and therefore the continuing influence on technological similarity is difficult to separate.

In addition, patents with no transferred inventors could be eliminated if resources permitted. Re-verification could more clearly display the probable effects of technological spillover from the mobility of inventors.

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