THE ROLE OF GENERAL PURPOSE TECHNOLOGY IN THE RESTRUCTURING OF MNC INTERNATIONAL INNOVATION NETWORKS

by

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ABSTRACT OF THE DISSERTATION

General Purpose Technologies in the Restructuring of International Innovation Network and Technological Diversification Strategy of Multinational Corporations

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This dissertation proposes to map the technological and geographical patterns of large multinational corporation (MNC) international innovation network, and explain its re-structuring process by involving the concepts of General Purpose Technology (GPT) and new Techno-Economic paradigm. The research adopts a multi-level approach focused on industry, MNC group, subsidiary and host country/region respectively. It is constituted by a case study and three interdependent empirical studies based on patent and patent citation data drawn from the USPTO Patent Database at Rutgers University. It suggests that internationalization of innovations of MNCs is closely linked to the development of GPTs in foreign subsidiaries. Innovations in GPT fields help firms re-allocate competence-creating activities to at least some foreign subsidiaries which become the new centers of excellence to these firms. More interestingly, only technologies in GPT fields which are outside of an industry's primary areas facilitate technological and geographical diversification of the firm's innovation network. GPTs in non-primary fields are also likely to increase the industrial diversification in the regions of host countries. This research, by linking the concepts of GPT to strategy and IB theory, addresses a gap in conventional MNC literature, which has been focused on internationalization or diversification. It also enriches subsidiary role literature.

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1.1 A Opening Case: Boeing's Aircraft Manufacturing in ICT ages

1.1.1 Introduction

Boeing is the world's largest manufacturer of commercial jetliners and military aircraft combined. Boeing designs and manufactures rotorcraft, electronic and defense systems, missiles, satellites, launch vehicles and advanced information and communication systems.

Boeing is in the aerospace manufacturing industry, in which processes and materials are distinguished from many other manufacturing industries by the stringency of the industry's requirement for safety, reliability and efficiency of operation of the goods it produces. In this industry, components need to be manufactured with greater accuracy and closer tolerances, and a high degree of attention has to be given to assembly. Parts are more customized, and are not the high volume commodity type of parts found in the automotive sector.

In such an era, technology and product life cycles are becoming ever shorter. Boeing is devoted in delivering most advanced products to customers. For instance, Boeing is currently developing a 787 Dreamliner program that will deliver the 787 into service in 2010. The 787 Dreamliners will carry 210 - 330 passengers on routes of 2500 to 8,500 nautical miles. During 2009, the US Defense Department had extended its research contract with Boeing to design and build a flying prototype for the Nano Air Vehicle (NAV) Program. The NAV Program will develop and demonstrate an extremely small (less than 7.5 cm), ultra-lightweight (less than 10 grams) air vehicle system with the potential to perform indoor and outdoor military missions.

As the technology used by the aerospace industry is complex and constantly changing, innovation is a route to future growth in the aerospace industry. Research and development (R&D) is an important factor for all aircraft manufacturers, allowing for product differentiation and more efficient production. R&D expenditure accounts for approximately 3% of industry revenue. It forms an integral part of the industry's activities, aimed at achieving improvements in product quality, efficiency and safety. The Engineering, Operations & Technology division of Boeing, helps develop, acquire, apply and protect innovative technologies and processes by providing innovative technology and process solutions, transforming Boeing into a global network-centric enterprise, enhancing and protecting the company's intellectual capital, and fostering a culture of innovation. Research and development in Boeing involve experimentation, design, development and related test activities for new and derivative aircraft and parts and any related activity.

The objective of this study is to show how some generalized technologies such as materials, industrial equipment, mechanical engineering and most recently the Information and Communication Technology (ICT) – improved design and manufacturing in Boeing company. This study is mainly based on literature review and some statistical analysis of patents granted to Boeing Co. in USPTO (U.S Patent and Trademark Office) in most recent decades.

1.1.2 Technology Development at Boeing and in the Aircraft Industry

In the Aircraft industry, R&D programs currently being undertaken by industry players are concentrated in the areas of: 1) propulsion systems: they emphasis on cost reduction, performance, efficiency and reliability while reducing the environmental impact of such systems (i.e. combustion, emissions and noise); 2) structures and materials focused on utilizing composite materials such as carbon-fiber and titanium while developing low cost manufacturing processes for aircraft structures (e.g. wing, landing gear and brakes); and 3) flight systems technologies associated with electronics, air traffic management, avionics, power systems, cabin environment and flight deck.

The focuses of the R&D efforts in modern aircraft industry are based upon the incorporation of Boeing's existing specializations in engines, power system and other aircraft-technologies with some technologies that are heavily applied in many other industries, such as such as mechanical engineering and materials engineering and general industrial equipment technologies. Boeing is the leader in improving their products and process by utilizing and developing such generalized technologies.

To build aircrafts and spacecrafts, materials with extremely high strength and low weight are necessary, such as titanium rich composite materials. Aerodynamics in both aircraft and spacecraft is an important factor to improve efficiency and reduce the cost of ownership. Reductions in the drag of an aircraft make direct contributions to both environment and cost saving. Furthermore, improvements in the lifting capability of aircraft during take-off and landing have a strong influence on safety and the environmental impact.

The industry is highly and increasingly dependent on investment in the computerization of systems and some other newest technologies. For instance, technology investments being pursued within Boeing include network-centric operations, affordable structures and manufacturing technology, lean and efficient design processes and tools, lean support and service initiatives - such as life cycle costing, advanced platform systems and safe and clean products.

1.1.3 New ICT-Related Technologies Developed and Adopted at Boeing

Boeing has utilized and developed some generalized technologies to design and build commercial and military aircrafts. Among them, the new emerged global Information Technologies (ITs) are playing an ever more critical role. They enabled paper-less design of the aircraft, reduced parts and rework, and ensured a reduction in the development cycle from 60 months to 48 months. The IT tools used in concurrent engineering include application programs, communications software, networks, frameworks, and database products. The use of CAD/CAM (computer-aided design and manufacturing) to build planes has become the norm. The use of 3D modeling software provides an understanding of design, layout and configuration options and can facilitate crucial purchase decisions.

Integration of CAD system and Widespread Availability of CATIA and EPIC

Boeing integrated its Computer Aided Design (CAD) systems using CATIA and Electronic Preassembly Integration on CATIA (EPIC) so that the 777 design teams from anywhere in the world can create virtual mock-ups instead of physical mock-ups. This provided key participants in the design process, ranging from airframe manufacturers in Japan, to engine manufacturers in the U.K. and U.S.

CATIA was used to design specific components. It allows engineers to design components in three dimensions and ensured that they would properly fit and operate before they were physically produced. EPIC allowed the different components of the aircraft to be designed and integrated into computer simulation of the whole plan. This eliminated the earlier habit of “throwing the design over the wall” and letting production worry about creating the equipment.

Create Fly-by-wire Flight Control System:

The FBW flight control system made it possible to use lighter wing and tail structures by obviating the need for complex and heavy mechanical cables, pulleys, and brackets. The pilot’s commands (through the control yoke) went to three control computers that formed the heart of the system. The system gave the pilot the important seat-of-the-pants feedback he/she would get from direct-link mechanical controls (Guy, 1995).

The payoff to Boeing using Information and Communication Technologies (ICTs) as a more advanced type of General Purpose Technologies in most recent decades has been in improving customer relations, tying in suppliers more closely in the production process, aligning IS with corporate goals and objectives, and increasing use of design-build teams all through the organization. The success of Boeing in integrating information technologies to improve production lead-times and quality, without even creating a mock-up of the Boeing aircraft, provides important lessons for other manufacturing companies. The lessons learned are that MIS needs to partner with design-build teams, include manufacturing workers in the teams, share knowledge, communicate with end-users, focus on customer needs, develop an appropriate IT architecture, and let end-users help develop content of the systems.

1.1.4 Other Generalized Technologies Developed and Employed at Boeing

Besides seeking for new opportunities using Information related technologies, Boeing tries to incorporate other generalized technologies. For instance, Boeing is planning to launch a new 787 Dreamliner to the market. This model is designed to provide airlines with unmatched fuel efficiency - the airplane will use 20% less fuel for comparable flights. Boeing has announced that as much as 50 percent of the primary structure - including the fuselage and wing - on the 787 will be made of composite materials. Also, Boeing is considering incorporating health-monitoring systems that will allow the airplane to self-monitor and report maintenance requirements to ground-based computer systems.

The improvement in materials is also critical to aircraft industry. In 2008, engineers from the University of Bristol in the UK developed a self-healing composite material for aircraft. In Portugal, Critical Materials SA is working on putting intelligence into materials to enable a monitoring system to detect faults and fatigue in aircraft material. Critical Materials' first project is an aircraft monitoring system capable of detecting problems in materials and reporting them, thus potentially saving on maintenance schedules while enhancing safety. These systems will not currently be able to deal with massive malfunctions such as explosions. Another four or five years are needed before the interactivity between monitoring and materials will be able to take place.

Moreover, Boeing is conducting a R&D project, employing Nano technologies to the design of a new generation of lightweight aircraft. In the Nano Air Vehicle (NAV) program, Boeing and its partners will explore novel, bio-inspired, conventional and unconventional configurations to provide the warfighter with unprecedented capability for urban mission operations. In June 2009, the R&D director is NAV program said its

Mercury NAV, a demonstrator that imitates winged creatures, had accomplished a technical first: the controlled hovering flight of an air vehicle system with two flapping wings that carries its own energy source and uses only flapping wings for propulsion and control.

1.1.5 Patent Analysis of the technological profile of Boeing

The Boeing case is focused on the corporate innovative activities in short period from year 1969 to year 1995 proxied by the patents granted to Boeing in USPTO system. The dataset includes 3006 patents that have been innovated by Boeing from all its affiliates in the world. Although the product line of Boeing is relatively less diversified, but a large amount of technologies are embedded in a single product. There are only about one third of the innovative activities are allocated to "Aircraft" technology field (Tech44), there are many other technology fields that Boeing is actively working with. Boeing is indeed developing technologies in almost all technology fields. Therefore, Boeing is what is called a "Multi-Technology" firm.

Table 1 shows the technological profile of Boeing's innovative activities from 1969-1995. The technology activities proxied by its patents are classified according to the U.S technology classes in USPTO (Table 1). The 27 years in our study are further divided into 6 periods. It is interesting to find that there has been a decrease in the core technology fields –"Aircraft" technology (Tech44) - from 33% in the peak period to 15% in most recent period. It implies that Boeing is taking more efforts in developing capabilities in the technology fields which are outside the core areas. For instance, there is an increasing proportion of patents have been found in the fields of "Synthetic resins and fibers" (Tech9, 0.5%-3.8%), "other organic compounds" (Tech 11, 0-1.1%), and

"Other general electrical equipment" (Tech39, 1.4%-4.4%). This is consistent with our earlier discussion that new materials and product process have been ever more important to aircraft industries. Moreover, some dramatic increases are found in the fields of "special radio system" (Tech 35, 2.9%-5.2) and "Office Equipment" (Tech41, 2.9%-10.7%). The latter observations further support our findings on the R&D efforts taken by Boeing in IT and related technology fields.

Among these fields in which we observe an increasing proportion of innovative activities in Boeing, many fields are found to have the "generalized" natures, such as synthetic resins and fibers, organic compounds, other general electrical equipment, and especially office equipment technologies. The latter is what we normally perceived as Information and Communication Technologies (ICT). These technologies are not concentrated only in aircraft industry, but have been widely applied and developed in many sectors in the economy.

[Insert Table 1 about here]

1.1.6 The Boeing's international R&D network

As an innovation led business, Boeing is continually looking globally for new ideas and technologies. Boeing has six advanced R&D labs across the US, and one overseas lab each in Australia and Spain - which together employ about 4,100 engineers.

U.K.

Boeing employs more than 600 people across the UK at numerous sites, and the UK remains a critically important market, supplier base and a source of some of the world's most inventive technology partners.

Boeing works with a number of universities in the UK and has established multi-year collaborative research and technology relationships. Each is focused on a different specific area of technology. For instance, with Cambridge University Boeing has an agreement to conduct a number of research projects in the field of highly networked systems. Cambridge is a recognized leader in IT research and this field is of particular interest to Boeing as it moves towards providing more integrated solutions to its customers. With Cranfield University, Boeing is working on a variety of projects on the design and production of a sub-scale demonstrator of a Blended Wing Body aircraft. At Sheffield University, Boeing is working with their Advanced Manufacturing Research Centre (AMRC) to develop advanced manufacturing technologies that will help reduce the cycle time and cost of producing aerospace products while improving their quality and performance. The AMRC has grown considerably since it was established and now has partners developing new manufacturing technologies that enhance the competitiveness of British industry across a broad spectrum of sectors – not only aerospace - but also marine, automotive and medical.

3D Modeling and Simulation Services have been heavily used in modern aircraft industries which employ the fully constrained parametric 3D solid models and assembly models developed from source data. The 3D Modeling and Simulation Services are used in the following areas: 1) Full Animation Sequences using 3D models are used to demonstrate equipment performance during engineering design processes; 2) Manufacturing Process Optimization using 3D Simulation are used to create virtual “What If” models to pre-test new manufacturing and assembly processes and reduce up-front investment in proposed process improvements. Models can be effectively combined with Lean assessment of processes for a full-circle understanding of the potential impact of proposed changes; etc.

Other projects include Weight Optimization, Discrete Design Optimization, Composites / Materials Engineering and Selection, and Materials Analysis. Weight Optimization is the modeling of design options to reduce equipment weight to lower shipping costs and improve operations efficiency, without compromising durability or reliability. Discrete Design Optimization is the development of options for improved equipment functionality and performance, with higher perceived value and lower total cost of operations. Composites / Materials Engineering and Selection is the modeling of equipment performance, peak failures, weight, repair/replacement procedures and other factors related to use of composites or other materials. Materials Analysis includes CFD (Computational Fluid Dynamics) Analysis, Thermal Analysis, Stress Analysis and Safety Analysis. It is used to support compliance with governing body specifications and regulations, including development of safety analysis reports.

Australia

In March 2008, Boeing established a branch of its advanced R&D unit in Australia, Boeing Research & Technology-Australia (BR&T-A), to provide a centralized R&D organization for Boeing's in-country businesses and serve as a focal point for collaboration with Australian R&D organizations, including universities and private sector R&D providers, the Commonwealth Scientific and Industrial Research Organization (CSIRO) and the Defense Science and Technology Organization (DSTO).

BR&T-A brings the best of Boeing technology to business pursuits in Australia by reducing technical risks on current programs and providing innovative technologies that enable the development of future aerospace solutions while improving the cycle time, cost, quality and performance of current aerospace systems.

Boeing’s Australian subsidiaries are continually finding opportunities to work with their Australian customers and R&D institutions to develop options for innovation, and as a result, BR&T-A’s research areas continue to evolve to address emerging customer and industry needs. Recent examples of Boeing driven R&D investments in Australia include: Unmanned Systems Research, Advanced Composite Components (produce new and improved resin to be used in the manufacture of advanced composite components), Biofuel Strategy Coordination and Advanced Manufacturing Research (new platform technology, with a focus on metals, titanium machining and improved tooling).

Bangalore, India

The India lab, Boeing's third of its kind outside the US, initially has 30 aerospace engineers working on multiple projects that include advanced aircraft and spacecraft designs and new structure and materials technologies. "Another 100 engineers will collaborate with our various projects being carried out with Indian academia, research and development (R&D) institutions and private and public enterprises," Boeing chief technology officer John J. Tracy told reporters at the unveiling of the lab here.

Clarifying that Boeing was not downsizing its operations in the recession-hit US or shipping projects to this country, Tracy said India's exceptional talent pool with high math quotient and analysis skill was the prime reason for locating its third overseas R&D lab in Bangalore.

"Core technologies are vital for global aerospace eco-system comprising R&D, engineering and IT (software). The criteria are to develop cutting-edge technologies to ensure affordability, breakthrough performance, sustainability and eco-friendly products and services to our customers worldwide," Tracy affirmed.

Beijing, China

Boeing is collaborating with three universities in China to develop wireless communication technologies employed in aircrafts. The subsidiary in China is also responsible to complete the improvement of Boeing-747/400 cargo aircrafts.

Boeing and the Qingdao Institute of BioEnergy and Bioprocess Technology (QIBEBT), Chinese Academy of Sciences, announced the establishment of a joint laboratory to accelerate microalgae based research leading to the commercialization of sustainable biofuels for the aviation industry in 2010 in Beijing. In addition, Boeing Research & Technology and the Chinese Academy of Science's Qingdao Institute of Bioenergy and Bioprocess Technology (QIBEBT) agreed to expand their collaboration to include other research institutions and aviation supply chain entities as part of their efforts on algae-based aviation biofuel development. The Joint Laboratory for Sustainable Aviation Biofuels will be managed by Boeing Research & Technology-China and QIBEBT, which will work together to place a strong emphasis on commercial applications for developed technologies.

Boeing has been at the forefront of sustainable aviation biofuel development throughout the world and is actively working with many different research institutes to realize regional solutions for a global need. The company is focused on sustainable biofuels produced from algae and other renewable resources that do not compete with food crops for land or water. Sustainable biofuels reduce greenhouse gas emissions over their life cycle while offering the potential to lessen aviation's dependence on fossil fuels.

To date, Boeing has helped establish biofuels research programs at 13 universities and institutions in the United States, Australia, Europe, the Middle East, India and China.

Boeing's R&Ds in other locations

Boeing's innovations and technology creation are not limited to its several research labs, but are active in many other locations. For instance, Boeing Commercial Airplane Group has signed a protocol agreement with the Russian Ministry of Foreign Economic Development to open a technical research center near Moscow that would employ Russian scientists and technicians in adapting Russian technology for Boeing's commercial aircraft business. Russia has expertise in metals, mathematics, aerodynamics and computer software. Boeing will provide the financing and other services to the joint-R&D project.

1.1.7 Patent Analysis on Boeing's international innovative activities

Boeing is the leading manufacturer of commercial aircrafts and military aircrafts in the world. Technologies are highly protected both by the company and by the government. Given this reason, Boeing's R&D activities have been much more centralized in the home country compared with firms in other industries.

Boeing tends to remain all critical technology developments in the U.S to secure the core competencies. As we have expected, amongst 3006 patents of Boeing in the period of study, only a few patents were innovated by the subsidiaries outside the U.S. However, there is a trend that an increasing proportion of innovations have been taken in Boeing's foreign subsidiaries, such as that in Germany, Canada, and other Middle-east countries. Moreover, when we link the internationalization of these innovative activities with the change in Boeing's technological structures, I find that those patents that have been invented in foreign countries are in the peripheral fields as we would expect, but are some technologies in the firm's field (Tech44). More interestingly, in more recent years, the innovations of such core technologies have been accompanied with the inventions in some supporting fields such as "Chemical processes" (Tech5), "Metal working equipment" (Tech 17) and "Other general industrial equipment" (Tech29). As we have discussed in previous section, some of these technologies are "generally" developed in many other sectors in the economy. This may suggest that the development of these "general" technologies is a critical condition to the re-allocation of the innovative activities of Boeing's core technologies, and consequently to the overall internationalization of the firm's R&Ds.

1.2 Dissertation Research Framework

As we have discussed, large multinational companies with multiple product lines and technological sectors like Boeing Co. are taking innovative activities in an increasing proportion of generalized technology fields. These technologies, such as materials, mechanical engineering, control system and the most recent Information Technology (IT) are lying outside the firm's core fields, but playing an ever more critical role in Boeing's innovations. Meanwhile, the R&D activities associated with these technology fields are not constrained at Boeing's U.S sites, but are active in a number of other Boeing's oversea presences, such as those in U.K, Australia, China and India. Boeing is doing so to take advantages of technological expertise of the host countries, in energy, biotech, mathematics and IT fields.

This dissertation research is focused on investigating the change of technological and geographical profile of world's largest manufacturers. This research is specifically motivated by the discussions of a new form of corporate innovations in the new technology paradigm and a recent debate over the extent to which the development of technological capabilities is still concentrated in the home country of **Multinational Corporations** (MNCs) (Patel and Vega, 1992; Granstrand, et al., 1992), or gradually dispersed across international innovation networks (Dunning, 1992; Pearce, 1992; Cantwell, 1995; Frost, 2001; Rugman and Verbeke, 2001). The concepts of "General Purpose Technologies" (GPTs), and the core technology (ies) of firms are brought into the context of the MNC innovation network literature. GPT has been defined as the technology that is "1) extremely pervasive in many sectors of the economy; 2) leads to continuous technical advance; and 3) requires complementary investment" (Helpman and Trajtenberg, 1998). A general research framework is shown in Figure 1.

[Insert Figure 1 here]

This topic is investigated under some basic presumptions. Firstly, a firm's core technology fields are basically the "primary" technology fields for the industry that the firm belongs to. The classification of core technology fields of firms and industries are constructed using equivalent method. Secondly, in general, a firm's core technologies are fairly stable over time. However, given that nowadays, firms need to build a wide technology base to compete with others and to deliver superior products to customers, over time, firms tend to take more efforts in developing technologies which are outside their primary fields. In other words, a decreasing proportion of technology activities in the firm's core fields implies that a firm is taking more efforts in developing other technologies, and consequently having a diversified technology profile. Thirdly, technology innovations proxied by patent creations in various locations of a multinational corporation show a trend of internationalization of corporate technology generation. Fourthly, the source of new technologies that the foreign subsidiaries of multinational corporations need to generation innovations includes intra-firm innovation networks and innovation activities outside firms, mainly in host countries. The latter can be proxied by inter-firm patent citations.

1.3 Research Questions

This research maps the technological and the geographical patterns of internationally integrated innovation networks of multinational corporations. We found that the geographical structure of MNC technological activities are determined by the "connective" nature of GPTs, the degree of centrality of these technologies within the MNC innovation network, and the linkage of these technologies to other technologies. The study addresses three broad questions:

First, in the context of a new techno-economic paradigm characterized by an increasing importance of science-based technologies, and more innovations based on fusions of formerly separated technologies (Kodama, 1992), do GPTs contribute to corporate technological diversification? and if so how;

Second, how does the development of GPTs contribute to the internationalization process of MNC competency creation worldwide? More specifically, we propose that when GPTs are a firm's core technologies they are still more likely to be developed at home, but that when they are adopted as a firm's complementary technologies, the development of these technologies has tended to become increasingly dispersed, given their "pervasive" and "enforcing" nature. Moreover, this dispersion over time can in turn help to explain a greater internationalization of a firm's core technology creation.

Third, how do GPTs affect the role of competency-creating (CC) subsidiaries within MNC innovation network and the relationship between foreign subsidiaries and host countries/regions? In core or non-core but non-GPT fields, is local subsidiary competence-creation development connected to GPT development as a means of bridging to the firm's core fields of activity? Does this occur in terms of intra-group cross-citation with GPT field development in other part of the firm located elsewhere? Are there variations between locations in terms of the likelihood of a co-location of non-GPT CC fields and GPT fields?

This dissertation research is composed in six chapters introduced by an opening case study in the change of technological and geographical pattern of Boeing's innovative activities in the world in Chapter 1. Broad research questions and some general description about data and methods are also addressed in this chapter. Chapter 2 is taken with an account of previous literature of corporate technological diversification, firm core technologies and the concepts of GPTs and new techno-economic paradigm, with a particular focus on how firms, through the development of GPTs, integrate dispersed capabilities while diversify their technologies within the multinational network, followed by the main contributions to existing literature in IB and strategy fields. From chapter 3 to chapter 5, I take three separate but inter-dependent empirical studies. In each study, I develop theories and propose hypotheses. I will also introduce the sample data employed by empirical analysis, the measurement of main variables and statistical methods in each study respectively, followed by statistical analysis and conclusions.

The three broad research questions are explored in three empirical studies. Study I and II are based on U.S patent (USPTO) data compiled and updated at University of

Rutgers[1]. The dataset covers patents granted in the U.S from year 1969 to year 1995, and further divided in three periods with nine years in each period. The data are organized as a panel of patents indexed by the period they are generated, the MNC group that the patent belongs to, the industry groups that the MNC group belongs to, the technology field that each patent is classified, and the countries of origin that the patent was generated. The country origin of each patent will be indicated according to the origin of the first inventor(s) listed in the USPTO system. Given that each patent might be created by the parent firm of a MNC group or the foreign subsidiaries of that MNC group, whether the patent was invented in “home” or “host” countries will be further coded.

Study III is focused on a subset of the data. We studied the technological activities of non-U.S multinational corporations in the U.S in the same period. By tracking patent citations of large MNCs in the U.S, we investigate knowledge accumulation of subsidiaries in foreign countries, as well as the knowledge interaction between MNCs in the same geographical clusters. By looking at citations, the third study builds upon the earlier analysis of the change in the technological and geographical patterns of corporate technological activity, suggesting that the degree to which firms can build international networks for innovative knowledge depends on a connection between development in GPT field and that in the their core fields. The uses of both patent and citation data also allow us to compare and contrast the cross-industry/firm measures of GPT fields developed here with the cross-field measure of the degree of generality of individual patents (held by firms or industries) as an alternative conceptualization of 'GPTs'. This comparison would be interesting and would represent a contribution in its own right.

[1] The dataset that has been created and update at Rutgers University cover patents granted in the U.S to the world’s largest industrial firms between 1969-1995, derived from both the Fortune 500 U.S and non-U.S firm listing (Dunning and Pearce, 1985). Patents have been consolidated at the level of international group of ultimate ownership, allowing for changes due to merges and acquisition since 1982.

Chapter 2. Literature Review

2.1 Corporate Technological Diversification

An important feature of firm evolution is diversification. Successful diversification has been found as reducing variability in the firm's profitability because earnings are generated from different businesses (Wang and Barney, 2006). **Diversification** refers to the extent to which a firm operates in multiple activities (Granstrand, 1998). Most times, it refers to product diversification or market diversification (Dewan, et, al, 1989), which mainly refers to the benefit firms taken from lower transaction costs and consequently economies of scope (Penrose, 1959; Teece, 1982; Montgomery, 1994)[2].

Whereas, compared with product diversification, technology diversification as an empirical phenomenon has attracted relatively little interest. Penrose (1959) has emphasized the importance of technology and industrial R&D as one of the sources for firm growth. Researchers follow (Pavitt, 1988; Pavitt, et al., 1989; Kodama, 1986) pioneered by Schumpeter (1976) has shed light on the ever-changing capital-consuming technology. Given that the viability of the firms increasingly steams from the long-run evolution of science and technologies, corporate technological competencies are believed to one of firm's key resources and dispersed over an ever wider range of sectors than the production activities (Granstrand, et al., 1997)[3], and technological diversification often

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[2] Granstrand (1998) has distinguished the business diversification (product, service and market diversification) from the resource diversification (technology diversification).

[3] Their data show that since from late 1980s, while world's large firms increasingly enter into such fields as materials, instrument controls, chemical process and calculators and computers, they existed from some traditional popular technological fields such as non-electronic specialized industrial equipment, bleaching, dyeing and disinfecting, etc this result is based on the assumption that the firm owns five or more patents

anticipates product and market diversification (Granstrand, 1998). Technological diversification has been found to have a positive relationship with firm performance (Gambardella and Torrisi, 1996; Henderson and Cockburn, 1996).

In a limited number of studies on technological diversification, the issue has often been studied from a static approach. The mail stream literature is to relate a firm's portfolio of businesses or technologies to a measure of relatedness or divergence (Hill and Hoskisson, 1987; Chari, Devaraj and David, 2008) or to investigate the management of diversified corporation (Jones and Hill, 1988). It is Kim and Kogut (1996)'s study that firstly suggested the importance of studying diversification from a dynamic approach. They proposed that a firm's diversification pattern corresponds to a broader so called "technological trajectory" (Nelson and Winter, 1977; 1982; Dosi, 1982) which either derives from acquisition of related knowledge outside of firms or from in-house innovation.

2.2 Core Technology Fields and Other Technology Fields

The concept of corporate technological diversification is often associated with the firm's core competencies. This is because as new opportunities emerge from general advances in science and technology, firms are on the whole becoming more technologically diversified over time, the technological competencies of the large firms depend heavily on the past and are fairly stable (Granstrand et al, 1997). The concept of core competency was early proposed by Prahalad and Hamel (1990). They believed that firms beat their competitors by their core products, and the latter are the physical embodiments of one or more core technological competencies.

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granted between 1985 and 1990.

The core competencies are defined as “a central set of problem-defining and problem-solving insights that enable firm to create potentially idiosyncratic strategic growth alternatives and enact to its environment” (Prahalad and Hamel, 1990). This concept is closely associated with the resource-based view literature. Rather than emphasizing products and markets, and focusing on competitive analysis on product portfolios, resource-based view regards the core competences as “a portfolio of competences”, and more recently, from technological approach (Prahaland and Hamel, 1990).

Similarly, evolutionary economists linked this concept to the “path dependent” character of corporate technology development (Nelson and Winter, 1982). It implies that firm’s core competencies in terms of technology and innovation are developed from organizational learning, and need to be evolved and changed through continuous organizational learning (Lei, Hitt and Bettis, 1996). Kim and Kogut (1996) made similar arguments, explaining the pattern of diversification as linked to a firm’s “platform technologies”. They suggested that a firm’s technological diversification could be derived from the “commonality” or the “complementarity” natures of the firm’s knowledge base. Therefore, there is a distinction between core diversifications and complementary diversifications. At this point, it is interesting to examine whether is firm’s technological diversification linked to firm’s core competencies? And if it is, are there specific technologies facilitating this diversification process?

2.3 GPTs, ICTs and New Techno-Economic Paradigm

2.3.1GPTs

General Purpose Technology (GPT) has been characterized as technologies that are

"1) extremely pervasive in many sectors of the economy; 2) lead to continuous technical advance with sustained performance improvement; and 3) require complementary investment" (Helpman and Trajtenberg, 1998). Given their nature of being pervasively and generally utilized, GPTs have been regarded as a "driving force" in corporate growth, especially technological progress over eras (Granstrand, Patel and Pavitt, 1997; Bresnahan and Trajtenberg, 1995). For instance, Granstrand and his colleagues (1997) observed that a large number of firms are mobilizing technological competencies in instrument and controls, chemical process, non-electrical machinery, computing and so on in order to make other products. These particular technologies could be generally used by firms from various industries, and are viewed as GPTs.

Schumpeter (1934) firstly pointed out that innovation takes place by "carrying out new combinations". Based on this assumption, Granstrand and Sjolander (1990) in their frame of reference identify specific technologies and link them to a firm's technological development. They argued that in "Multi-technology Corporation" technological opportunities are increasingly generated in a fundamentally important way through the combination and re-combination of various technologies, new and old. Such a process of combination and recombination is actually eased by firm's specific technologies which could be combined or integrated, and also vary over time, and these activities lie at the heart of the invention and innovation (Granstrand, 1998).

With the invention of computer and internet, evolutionary economists suggested that a widening range of technological opportunities have derived from Information and Communication Technologies (ICT) (Granstrand, et al, 1992; Oskarsson, 1993; Patel and Pavitt, 1991), and a new ICT-based techno – socio - economic paradigm has emerged.

Thanks to these technologies, there is the emergence of an extended trajectory of incremental technical improvements, the gradual and protracted process of diffusion into widespread use, and the confluence with other streams of technological innovations. Given above discussions, we believe that ICT is indeed an advanced type of “General Purpose Technologies”.

The new ICTs and related technologies-based paradigm, compared with the old paradigm which is energy- and oil-related technology based, is characterized by the pervasiveness of ever more complex technologies, the increasing importance of science-based technologies (Dosi, 1982; Freeman and Perez, 1988; Cantwell and Fai, 1999; Cantwell and Santangelo, 2000), and the fusion of formerly separated technologies (Kodama, 1992). Firms as the main actors in the evolution of new technological paradigm, tend to further reinforce the development of ICTs to support an even more widely dispersed network of differentiated creativity (Cantwell and Santangelo, 2000). As GPTs, ICTs are viewed as a ‘carrier branch’ in the new techno-economic paradigm (Freeman and Perez, 1988), or as the ‘catalyst’ of the fusion of formerly separate technologies (Kodama, 1992). However, very few studies have studied these two concepts together; neither have they linked these specific technologies to firm’s technological diversification.

2.4 Internationalization of Corporate R&D and Integrated Innovation Networks of MNCs

Large multinationals have become involved in an international technological diversification over the past decades (Cantwell and Piscitello, 1996; Patel and Pavitt, 1998). Empirical evidence[4] indicates that foreign locations have come to account for a leading or dominant position in close to 25 percent of all technology generations (Zander, 1997). It has been suggested that the integration or recombination of technology within the multinational network increasingly takes place within individual locations, because foreign units have been found to gradually increase the number of technologies they are involved in (Zander, 1997). However, the studies do not allow for an assessment of the degree of relatedness between dispersed technological capabilities or the extent to which technological knowledge is actually exchanged across locations.

While some studies (Patel and Vega, 1992; Granstrand, et al., 1992) emphasized that the technological activities of the world's largest firms continue to be firmly embedded in, and influenced by, the conditions in their home countries, a lot more others pioneered by Vernon (1979), suggested that increasingly more technologies are generated from countries outside a MNC's home country (Dunning, 1992; Pearce, 1992; Cantwell, 1995; Frost, 2001; Rugman and Verbeke, 2001; Frost, et al., 2002), especially in high-technology industries (Almeida & Phene, 2004; Frost and Zhou, 2005). Moreover, competitively stronger MNCs are more likely to locate R&D abroad, and to evolve toward a greater variance in the levels of R&D across their subsidiaries (Cantwell and Kosmopoulou, 2002).

The internationalization of corporate innovation activities is not uniformed across all firms. The determinants of this internationalization and the evolution of foreign technological capabilities have been summarized as: 1) the market conditions when the firm expands (Zander, 1998) – host country factors; 2) the management attitudes towards internationalization as well as the amount of operational and technological freedom

[4] Swedish multinational corporations

granted to foreign subsidiaries (Behrman and Fischer, 1979) – parent firm and subsidiary factors; and 3) the underneath path of expansion determined by product characteristics or industry affiliation (the industrial groups) – industry characteristics. Therefore, the international dispersion of technological capabilities may involve significant variance even across firms in similar lines of products.

Evolutionary economists (Kogut and Zander, 1993, 1995; Cantwell, 1991; Dunning and Narula, 1995; Pearce and Singh, 1992; etc) explained the reasons of why technology is developed in international networks rather than in a series of separately owned plants from the very nature of technological development approach. They argued that it is because of the need to monitor new technological development and to generate new value-creating technological capabilities distant from that of the home countries. The value-added activities in the subsidiary level are further eased by the fact that host countries are becoming increasingly specialized in generating specific technologies (Freeman, 1987; 1995). For instance, empirical study has found that locations such as USA, Germany and U.K continue to become ever more important for multinational corporations (Patel and Vega, 1999).

While a number of scholars argued that given the ever more complex nature of technologies and broader knowledge background, firms should have a rather disintegrative knowledge generation mechanism, some others (Chesbrough and Teece, 1996; Granstrand, Patel and Pavitt, 1997) casted doubts on this assertion, pointing out that full-scale disintegration might be ineffective and dangerous given that firms might lose their core competencies. At this point, MNCs may disintegrate the knowledge generation sources while maintain their technological specialization by locating the innovation facilities in an ever broader range of host countries; while systematically integrate the components and sub-system of product and process changes through their international innovation network (Ghoshal, Korine and Szulanski, 1994). This argument is consistent with the contingency theory, the internal structure within a multinational corporation will not be homogeneous, but will be differentiated to match the contexts of its different national subsidiaries (Lawrence and Lorsch, 1967). Thus Ghoshal and Nohria (1989) tried to identify the headquarter-subsidiary relations and proposed a “fit” governance structure.

Therefore, it has been argued that the production and technological generation mechanism of MNCs has thus been shifted from independent locally oriented affiliates towards global or rationalized networks (Hedlund, 1986; Porter, 1986; Bartlett and Ghoshal, 1989). Large MNCs which are assumed as technology leaders are now developing an international intra-firm network to exploit the locationally differentiated potentials of each subsidiary (Cantwell 1995; 1994; 1991; Cantwell and Barrera, 1995). From the host country perspective, the globalization of technological innovation in MNCs, in the sense of an international integration of geographically dispersed and locally specialized activities will in turn reinforce but not to dismantle nationally distinctive patterns of development (Cantwell, 1995).

Empirical evidence of knowledge seeking activities of the large MNCs in foreign countries mainly comes from the studies of research-intensive industries. For instance, Kuemmerle (1999) argues that firms in biotechnology establish R&D facilities to both “exploit” and “augment” their R&D capabilities. Almeida (1996) shows that foreign firms in the semiconductor industry cite same-region patents more often than local firms, which suggests that foreign firms make greater use of local knowledge than local counterparts. Moreover, Florida (1997) finds that accessing new indigenous technology is more important than customizing existing technology for new markets in a sample of 207 foreign research laboratories in the United States in biotechnology/drugs, electronics, chemicals/materials, and automotive. These evidences showed that the location choices of R&D activities within large MNCs may have heterogeneous motives across industries. Chung and Alcacer (2002) found that knowledge-seeking activity is limited to only R&D intensive industries. Foreign firms investing in pharmaceuticals, semiconductors, and electronics have positive valuations, while firms investing in chemicals have negative valuations of state R&D intensity.

Summarily, although research appears to confirm an overall trend towards increasing technological diversification of the large multinational corporations (Pavitt, et al, 1989; Oskarsson, 1993), and suggests that the geographical dispersion of R&D co-evolves with corporate technological diversification (Breschi et al, 1998; Cantwell and Piscitello, 1999; Zander, 1997), there is only limited knowledge about the rationale behind the evolution of MNC international integrated network, and moreover, the technological pattern of this network.

Among very few studies in this area, Santangelo's study (1998) has demonstrated that the growing geographical dispersion of intra-firm networks is linked to an increase in corporate ICT specialization. Most studies in the area were concentrated on the contributions of the advanced information technology to the effective management of international R&D and cross-border innovation. Patel and Vega (1999)'s empirical study shows that firms are active outside their home countries in the 'high technology' fields

(Computers, Pharmaceuticals, Telecommunications), and quite a sizeable proportion of these foreign activities are concerned with process and machinery technologies. Vertova (2002)'s study stressed that the change on different stage of the technological paradigm has always been accompanied with the change on the structure of geographical distribution. Cantwell and Santangelo (2000)'s study found that in the new paradigm, multinationals tend to develop abroad technologies which are less science-based. They also proposed within the science-based industries, firms may also generate abroad some technologies which are heavily based on tacit knowledge, but outside their core technological competencies. Their more recent study (2006) further showed that some close inter-related technology development is usually relied on MNC's intra-firm networks.

However, none of these studies provided a systematic analysis on how do MNCs re-allocate their technological efforts and in accordance with the needs to improve the efficiency and effectiveness of their international innovation network, and this question deserves further attentions.

2.5 Subsidiary Knowledge Accumulation and Subsidiary Roles

Even though the internationalization of advanced technological capabilities often implies a shift from the traditional home-centered configuration, the process does not necessarily imply increasing exchange of knowledge across the dispersed units. Empirical studies have distinguished international duplication from international diversification (Zander, 1999), but they also admitted that these two processes of advanced technological capabilities often go hand in hand.

In recent years, linked to the close integration of subsidiary into international network within MNCs, subsidiaries have gained a more creative role, generating new technologies in accordance with the competitive advantages of the country they are located (Cantwell, 1989, 1995; Pearce, 1997; 1999; Zander, 1999). Since the mid 1980s, a growing stream of research shows interests on the management of headquarters-subsidiary relationships, and in particular on the systems MNCs use to coordinate their network of subsidiaries (Bartlett and Ghoshal, 1989; Ghoshal and Nohria, 1989). From the 1990s, a large number of empirical studies start to deal with subsidiary role questions (Harzing and Noorderhaven, 2006; Ambos and Reitsperger, 2004; Birkinshaw and Morrison, 1995; Nobel and Birkinshaw, 1998, Gupta and Govindarajan, 1991; etc).

A recent strand of literature has tried to differentiate the foreign subsidiaries which exploit parent firm competencies from those which are comparatively independent and explore new competencies, through tracking knowledge flows among MNCs units. For instance, Ghoshal and Bartlett (1988)'s study identified the tasks of affiliates according to their research abilities and roles within MNC network. They categorized the roles of subsidiaries into: creation, adoption and diffusion. Gupta and Govindarajan (1991) create a knowledge-flow-based construct – through which they define four generic subsidiary roles: Global innovator (high outflow, low inflow), integrated player (high outflow, high inflow), implementer (low outflow, high inflow) and local innovator (low outflow, low inflow). Similar categorization can be found in Ambos and Reitsperger (in press)'s study which distinguish between technological mandate (outflows) subsidiaries and task-related interdependence subsidiaries (inflows and outflows). Moreover, Birkinshaw and Morrison (1995) have provided a three-fold typology to classify subsidiaries into local implementer, specialized contributor and world mandate. Similarly, Pearce (1999)'s study, through distinguishing subsidiary-level capabilities, characterizes the differentiation between world product mandate and regional product mandate.

Cantwell and Janne (1999)'s study on European subsidiaries made efforts around the same topic, but from a different approach. In their study, the research activities by foreign facilities are distinguished as either 'replication' or 'diversification'. Almeida (Almeida, et, al., 2003) studied the same question through unbundling the process of knowledge management of multinationals by identifying its components: search, transfer, and integration, and to link firm's capabilities associated with each stage of this process.

Furthermore, distinct from early literature which viewed subsidiaries as "appendages" of the MNC in many American firms or as largely independent entities in the case of European firms (Stopford and Wells, 1972), recent research (Bartlett and Ghoshal, 1989; Ghoshal and Bartlett, 1994) views MNC as a globally integrated but differentiated network, and emphasizes the interdependence nature of subsidiaries within MNC. For instance, Kogut and Zander (1993) viewed MNC as a social community which transfer and recombine knowledge created by its sub-units.

Based on these findings, there have been emerging interests on the "exploration" role of some foreign subsidiaries. The concepts of 'center of excellence' and 'competence-creating subsidiary' remedy the subsidiary focus of the earlier view. These terminologies have been referred to those subsidiaries which bear strategic role in the corporation (Bartlett and Ghoshal, 1986), and embody a set of capabilities that has been explicitly recognized by the firm as an important source of value creation (Frost, et al., 2002). Multinational subsidiaries significantly acquire local technologies to 1) offset home country weakness (Almeida, 1996); 2) monitor and assimilate foreign technology

Hakanson and Nobel (1993); and 3) supply technology which is complementary to the primary technological capabilities available in the home market (Cantwell and Randaccio, 1992). Phene and Almeida (2003) then found positive changes in the scale and scope of innovative activity across time, which suggest the subsidiary-level technological diversification.

In this context, it is argued that subsidiaries with competence-creating mandates can arise from either parent-driven or subsidiary-driven processes (Birkinshaw and Hood, 1998). In other words, while some scholars emphasize the internationally integrated MNC at a group level (Doz, 1986; Hedlund, 1986; Porter, 1986; Bartlett and Ghoshal, 1989), some others (Pearce, 1999; Kuemmerle, 1999) developed a typology for subsidiary-level R&D in which the drivers of R&D diverge between subsidiary types.

Studies have examined the creation of firm-specific advantages through knowledge transfer within the MNC (Gupta and Govindrajan, 2000; Hansen and Lovas, 2004).Ronstadt (1977) has observed that a majority of the foreign labs in his study followed an evolutionary path from performing technology transfer to support local sales to becoming a global technology center. The theoretical foundation for internationally interdependent R&D is consistent with the models of “Heterarchy” (Hedlund, 1986) or “Transnational” corporations (Bartlett and Ghoshal, 1988; 1990).

However, only Zander (1997, 1998) has suggested that advanced technological capabilities related to individual technologies have become increasingly geographically dispersed over time in his studies of Swedish multinationals. Most other discussions on subsidiary roles in MNC international innovation networks, as we discussed above, are simply focused upon the distinction between competence-exploiting and competence-exploring (competence-augment) activities of foreign subsidiaries. For instance, Cantwell and Mudambi (2005)'s study is mainly focused on identifying some general determinants of the competence-creating (CC) type of foreign subsidiaries from host country and parent firm approaches, while the underlying sectoral patterns of the technological activities that subsidiaries are taking are still lacking of attentions. In other words, studies on intra-firm knowledge transfer motivated by technological diversification are still in infancy.

2.6 Potential Contributions to the Literature

Our study contributes to the existing literature in a variety of ways. Firstly, the term of General Purpose Technology has early been introduced in economics literature. Although GPTs and the new techno-economic paradigm have been uncovered and defined (Granstrand, et al, 1992; Oskarsson, 1993; Patel and Pavitt, 1991), GPTs and ICTs have always been studied as separate concepts. The studies on the development of GPTs, especially GPTs in the new techno-economic paradigm (ICTs) are still in their infancy (Santangelo, 2002; Cantwell and Santangelo, 2002; Cantwell and Santangelo, 2000). Moreover, the term of General Purpose Technology has been mainly found in the economics literature (Helpman and Trajtenberg, 1998; Bresnahan and Trajtenberg, 1995). Later studies are mainly focused on the contributions of GPTs to the economy as a whole. We know little, however, the research of GPTs in the organizational context such as the firm's absorptive capacity and technological diversification. The linkages between the natures of these driving force technologies and firm technological structure and the strategic issues have been paid only limited attentions (Breschi et al., 2003).

In addition, the corporate diversification issue has usually been investigated from a static viewpoint – focused on product/business diversification or technological relatedness at some given point or period in time. Although a few studies have appeared to confirm an overall trend towards co-evolution between the geographical dispersion and corporate technological diversification (Cantwell and Piscitello, 1999; Zander, 1997) within large MNCs, we still know very little, however, about the sectoral pattern of this technology internationalization process (Cantwell and Kosmopoulou, 2001). This study, based on panel data covering 27 years attempts to shed light on the dynamism of the interaction between the technology progress and the globalization within the MNC international network.

This dissertation research, by linking GPTs to the location of MNC technological creations, addresses a gap in the conventional MNC strategy literature, which has been focused either on internationalization or on technological diversification of MNCs. Although few studies seem to suggest a co-evolution of geographical dispersion of R&Ds with corporate technological diversification (Breschi et al, 1998; Cantwell and Piscitello, 1999; Zander, 1997), we know relatively little, however, about the rationale behind the emergence and dynamics of such international innovation networks. While most studies on the location of MNC innovation are focused on host country characteristics, our study suggests that the technological strategy of the firm matters too.

Chapter 3. Concepts and Measurements of GPTs

3.1 Concepts of GPTs

3.1.1 GPTs

Following the resource-based view literature on firm growth, one approach to study corporate technological diversification is to examine the development of a firm's underlying technological trajectory. We'd like to introduce a concept of the so called "General Purpose Technology". It has been observed that there exists a set of "'General Purpose Technologies' (GPTs) characterized by the potential for pervasive use in a wide range of sectors and by their technological dynamism" (Landes, 1969; Rosenberg, 1982; Bresnahan and Trajtenberg, 1992). Jame Watt's steam engine is an early example of such technologies that fulfilled this technology role in the first industrial revolution. Many other technologies or technological areas have been studied as GPTs in literature, such as non-electrical machinery (Rosenberg, 1976), instrument and controls, chemical processes, computing and so on (Granstrand et, al., 1997), which have been actively mobilized in a wide range of firms in different industries.

More recently, scholars formalized the concept of "generality", charactering it not only with a wide range of users, but with a technological cumulativeness, dynamism and complementarity innovations (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998). **General Purpose Technology (GPT)** in this dissertation is thus defined as the technology fields in which technologies have been applicable to a wide range of industries.

GPTs have early been studied in economics literature, which is mainly focused on the contributions of these technologies to the general economic growth. In spite of the long tradition in GPT studies, which are well rooted in economics literature, our understanding of GPTs is still limited. Previous studies on GPTs have tried to be focused on growth accounting of specific examples of GPTs using case study, or associate GPTs with general technological and economic growth. We need greater in-depth studies on the linkage between GPTs and firm strategies and corporate evolution.

Given their nature of being pervasively and generally utilized, GPTs have been regarded as a "driving force" in corporate growth, especially technological progress over eras (Granstrand, Patel and Pavitt, 1997; Bresnahan and Trajtenberg, 1995). For instance, Granstrand and his colleagues (1997) observed that a large number of firms are mobilizing technological competencies in instrument and controls, chemical process, non-electrical machinery, computing and so on in order to make other products. These particular technologies could be generally used by firms from various industries, and are viewed as GPTs.

Schumpeter (1934) firstly pointed out that innovation takes place by "carrying out new combinations". Based on this assumption, Granstrand and Sjolander (1990) in their frame of reference identify specific technologies and link them to a firm's technological development. They argued that in "Multi-technology Corporation" technological opportunities are increasingly generated in a fundamentally important way through the combination and re-combination of various technologies, new and old. Such a process of combination and recombination is actually eased by firm's specific technologies which could be combined or integrated, and also vary over time, and these activities lie at the heart of the invention and innovation (Granstrand, 1998).

Strategy literature on technology market has tried to study GPTs from supply side, examining the producer firms of GPTs, and suggested a positive relationship between GPTs and corporate specialization in Biotech and Software industries. Firms in these industries modularize their technology, enabling them to change the business model to sell general purpose research or production tools to different buyers [5](Giarratana, 2004). But these evidences are limited to entrepreneurial and start-up firms. At this point, it is particularly interesting to look at the large multi-technology firms as both suppliers and users of GPTs, and more important, how these innovations help change corporate technological and organizational structure?

3.1.2 New Socio-Techno Paradigm and ICTs

Nowadays, the theoretical development of such ‘connective technologies’ have been fitted into the new research context. Similar with Vernon (1966)’s product life cycle model, Vertova (2002) proposed a “technological cycle” model which steams from the concept of technological paradigm. The concept of technological paradigm has been introduced as a cluster of innovations, based on a common set of scientific principles and on similar organizational methods, and associated over time with particular economic, social and institutional mechanism (Cantwell and Santangelo, 2006; Freeman and Perez, 1988; Dosi, 1984). This concept has been originated from Dosi (1982) pioneering work on the analogy between the scientific and the technological paradigms. This scientific and technological paradigm has then become techno-economic paradigm (Freeman and Perez, 1983, 1985) taking social and institutional factors into concerns.

With the invention of computer and internet, evolutionary economists suggested that

[5] They found that some firms patented generic encryption algorithms that they can license in very heterogeneous ways.

a widening range of technological opportunities have derived from Information and Communication Technologies (ICT) (Granstrand, et al, 1992; Oskarsson, 1993; Patel and Pavitt, 1991), and a new ICT-based techno – socio - economic paradigm has emerged. Thanks to these technologies, there is the emergence of an extended trajectory of incremental technical improvements, the gradual and protracted process of diffusion into widespread use, and the confluence with other streams of technological innovations. Given above discussions, we believe that ICT is indeed an advanced type of "General Purpose Technologies".

The new ICTs and related technologies-based paradigm, compared with the old paradigm which is energy- and oil-related technology based, is characterized by the pervasiveness of ever more complex technologies, the increasing importance of science-based technologies (Dosi, 1982; Freeman and Perez, 1988; Cantwell and Fai, 1999; Cantwell and Santangelo, 2000), and the fusion of formerly separated technologies (Kodama, 1992). Firms as the main actors in the evolution of new technological paradigm, tend to further reinforce the development of ICTs to support an even more widely dispersed network of differentiated creativity (Cantwell and Santangelo, 2000). As GPTs, ICTs are viewed as a 'carrier branch' in the new techno-economic paradigm (Freeman and Perez, 1988), or as the 'catalyst' of the fusion of formerly separate technologies (Kodama, 1992). However, very few studies have studied these two concepts together; neither have they linked these specific technologies to firm's technological diversification.

Studies on ICTs have discussed the beneficial effects of ICTs in firm diversification, suggesting that ICTs facilitate corporate diversification by enhancing intra-organizational control and coordination (Dewan, Sanjeev; Michael, 1998). There is lack of evidence, however, that how these generalized technologies help widen corporate knowledge base and consequently change corporate technological structures.

3.2 Measurement of GPTs

3.2.1 Measurement of GPTs in Literature

In addition to case studies on specific technologies, patent data have been mostly used to measure GPTs. Some most acknowledgeable work including Hall and Trajtenberg (2004)'s study on the classification of GPTs based on a large number of U.S patents. In their study, GPTs have been selected from three million patents in USPTO that have been mostly cited in the period of study. The authors suggest a series of measurements of GPTs such as generality, frequency, patent class growth and citation lags. By contrast, Cantwell and Santangelo (2000, 2002) studied innovation issues in the new techno-economic paradigm (Information and Communication Technology) based on U.S patent Data.

Patent statistics has been widely recognized as a potentially reliable source to study the questions on technology structure across countries, industries and firms (Freeman, 1982; Pavitt, 1988; Griliches, 1990). The use of patent stocks is not limited to the direct measure of new technology creation, but can be extended as a proxy for the underlying pattern of technological change, given the cumulative, incremental and path-dependent process of technological evolution (Nelson and Winter, 1982; Rosenberg, 1982; Dosi, et al, 1988; Cantwell, 1991). Patent data have been used in empirical studies covering many industries, such as semiconductor industry (Kim and Kogut, 1996), pharmaceutical industry (Chuang and Alcacer, 2002) and biotechnology industry (Shan and Song, 1997).

Distinct from Hall and Trajtenberg's measurement, which is based on the classification derived from some single highly cited patents, the classification of GPTs in this dissertation research is based on a field approach. More specifically, we define GPTs as technologies (patents) in some broad technology fields, which, as compared with patents in other technology fields, tend to be more generally applicable. By using the field approach,

3.2.2 Measurement of GPTs Using Patent Data

The classification of GPTs in this dissertation study is based on the USPTO patent data compiled and updated at Rutgers University. It covers patents granted to the largest MNCs in the world from year 1969 to year 1995, and being further aggregated into three periods of nine years each. The total 948, 190 patents created by all largest industrial firms in the world are organized as a panel dataset indexed by the period they are generated, the MNC group the patents belong to and the technology field the patents are assigned to respectively.

Technology Creation Approach

We first classify GPTs on a cross-industry technology creation approach. GPTs are thus defined as the technology fields, in which patents have been created by firms from a wide range of industries. Patents in our dataset are firstly grouped as belonging to a common corporate group of firms where they were assigned to affiliates of a parent firm. Each corporate group is in turn allocated to an industry on the basis of its primary field of production (Cantwell and Andersen, 1996). All firms are then assigned to one of the 16 industrial groups which are shown in Table 4. Moreover, to study various technologies created by each industrial group, each patent is allocated to one of 399 technological sectors (the type of technological activity with which each patent is most associated), which in turn belong to one of the 56 technological fields (Cantwell and Andersen, 1996). Normally each patent class is assigned to a distinct technological sector, but in some case classes are sub-divided between fields, thus the fields to which a given class contributes may fall under quite different technological groups. To illustrate this point, a chemical company increasingly needs to draw on knowledge and skills in many diverse areas, such as mechanical, electronics and biotechnology to further develop its own process system, even if it has no intention of entering markets that are primarily based on these technologies.

By now, the sectoral classification of patents and the industry of the firms to which patents were assigned have been recorded separately. In our study, the use of the term “technology (ies)” or “technology field (s)” referring to one of the 56 technology fields, and the term “industry” or “industrial group of firms”, referring to groups of firms are differentiated. Most large firms have engaged in the development of more than one technological sector. Patents in each industry group will therefore distribute across many technological fields. Similarly, because technologies could be combined and adopted to serve various products and markets, patents within each technological field are usually across many industries. The 56 technological fields and 16 industries are listed in Table 3 and Table 4 respectively.

[Insert Table 3 and Table 4 about here]

Our measurements of GPT fields in a given industry are based on a two-dimensional construct which takes into account both the size of technological effort by the firms of an industry in some field, and its degree of dispersion across the firms of different industries (Table 5a, 5b and 5c). Similar methods have been adopted in Granstrand (1997)’s study on the corporate technological competencies[6] or Cantwell and Andersen (1996)'s work on corporate technological leadership and technological specialization[7].

[Insert Table 5a, 5b and 5c about here]

To identify GPT fields and the primary technological fields of each industry, we firstly create a 16x56 table in which each cell shows the number of patents granted to firms in a given industry and belonging to that technological field. Based on this matrix, the share of patents of each technological field within each industrial group, and the share of patents of each industry within any given technological field can be calculated. The share of technology fields in each industry (*Tech_Ind*) and the share of industries in each technology field (*Ind_Tech*) respectively are defined as:

$$Tech\_Ind = P_{ij} / \sum_j P_{ij}$$
$$Ind\_Tech = P_{ij} / \sum_i P_{ij}$$

Where Pij denotes the number of patents granted in industry i and technological field j. It is found that almost all industries are developing some technologies from all fields, and in turn almost each of the 56 technological fields is generally used in all 16 industries.

To identify GPT fields in this study, we have adopted the criteria that: firstly, compared with other technologies, the GPT field should be distributed relatively evenly across many industries; and secondly, the overall size of activity in that field should be large enough. These criteria operationalized by selecting technological fields in which there are more than six (out of sixteen) *Tech_Ind* shares that are greater than or equal to

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[6] They created a fourfold classification framework in which the y-axis and the x-axis ranked dispersion of the absolute patent share of technical fields in a firm and ranked the firm's RTA across fields index respectively.
[7] They investigated corporate technological leaderships and corporate technological specialization through measuring the sectoral distribution of patents in each industry and industrial distribution of patents in each technological field respectively.

3%. We choose 3% as the threshold because it is close to the mean value of the share of technological fields across industries (Table 6). In this way, we identified 9 technology fields out of 56 as GPT fields (Table 7). Namely, these GPT fields are tech5-chemical process, tech9-synthetic resins and fibers, tech11-other organic compounds, tech16-chemical and allied equipment, tech29-other general industrial equipment, tech38-electrical devices and systems, tech39-other general electrical equipment, tech41-office equipment and tech53-other instruments and controls.

Furthermore, we found that among the 9 GPTs, the sectors of office equipment (tech 41) and other instrument and controls (tech 53) have higher growth rates compared with the other 7 technological fields. These two technology fields are literally ICTs, which are also consistent with the theoretical definition in previous discussion and other literature (Santangelo, 1998; Cantwell and Santangelo, 2000), that they are conceived as the GPTs in the new techno-economic paradigm (ICTs). By contrast, the other 7 technologies are viewed as GPTs in the old paradigm given that their growth rate is either negative or lower.

[Insert Table 6 and Table 7 about here]

Citation Analysis on Creation-based GPT Classifications

Since most previous studies (Hall and Trajtenber, 2004) are primarily based on patent citations, we compare technology creation-based measurement on GPTs with the citation-based approach. The citation data are taken from all large industrial firms from non-US countries and their subsidiaries in the U.S from 1969 to 1995, as well as the citations of these patents back to 1890. The dataset includes 77,851 patents that have been innovated by the U.S affiliates of largest foreign firms in the USPTO system (the

United State Patents and Trademark Office) from 1969 to 1995. We also track totally 135,084 patents that have been cited by the formers. All patents and patent citations are from a database that have been created and updated in Rutgers University.

The citing patents are organized as a panel of patents indexed by the year of being granted, the MNC group to which the patents belong, the technology field that the patenting activities are classified in USPTO system, the country of origin of each MNC, and the U.S state that the patents have been invented. The country of origin and the U.S state of each patent are identified by the location of the first inventor(s) in that patent. The data thus include patents of over 300 MNCs that are originated from about 20 countries in the world. For citation data, we only record the technology classification and granted year for each cited patent in study.

Table 8a shows the backward and forward citation frequencies of technologies in all 56 fields. Number of backward citations shows the average number of cited patents that a group of citing patents refers to that are from same technology field. Number of forward citations shows the average number of citing patents that have cited a certain group of cited patents that are from same technology field. For instance, we found that patents in tech23 (mining equipment) have most backward citations in average compared with patents from other fields, and patents from tech54 (wood products) have least been cited by other innovations. Unlike what we have expected, there is no direct linkage of citation frequency and the generality of knowledge creation. Most of the defined GPT fields show a relatively low citation numbers compared with other fields.

This is probably due to the fact that GPT fields have larger sizes compared with other technology fields in terms of number of patents. This may lower the average value of patent citations if there exist a large number of patents with single or fewer citations. We correct the bias by dropping the citing patents that have less than 7.8 backward citations, and the cited patents that have less than 1.4 forward citing patents. Table 8b shows a more consistent result. More specifically, we found that tech5, tech9 tech 11, tech 16 show higher values of citation frequency in terms of both backward and forward citations compared with other fields. However, the citation numbers in tech 29, tech 38, tech39, tech41 and tech53 are relatively low. A possible explanation is that, as we discussed, these fields are newly emerged in more recent years, and it takes a fairly long period of time for technology diffusion. With more updated data, we may found some different result in this analysis.

[Insert Table 8a and 8b about here]

3.2.2 Technology Application Approach

Furthermore, as we have mentioned in the earlier section, a major contribution of this study is to complement the measurement of GPTs in existing literature. In this dissertation research, we adopted both cross-industry measurement and cross-field measurement on GPTs, comparing and contrasting the two approaches. Unlike in the previous section, in which we define GPTs as being “generally created” by firms across many industries, in this section we define GPT fields as technology fields in which innovations have been widely applied. In other words technologies in GPT fields have a wider technology base compared with technologies in other sectors. More specifically, we investigate whether patents in certain technology fields are based on the citations of patents from a wide range of technology fields.

This measurement is based upon the patents and patent citations of all largest foreign firms in the U.S from 1969-1996 as we described in previous section. We classify the GPT fields based upon a Generality Index which calculates the "degree of generality" of each technology field by examining whether the citation activities in a given field cover a wide range of technology sectors. The Generality Index measurement is similar to the Hall and Trajtenber (2004) 'Generality' measure, which is defined in the following way:

$$GI = GeneralityIndex = 1 - \sum_{i}^{nj} S_{ij}^{\ 2}$$

where Sij denotes the percentage of citations received by cited patents i in technology class j, out of ni citing patent classes. We thus measure the degree of generality of the cited patent technology classes. Given that the citation activities in our sample data only cover a short period of time up to 1995, in which some new emerging technologies such as ICTs are still in their infant stage, the citations of technologies in such fields (Tech 41 and Tech 53) might be biased downward our result. Therefore, we also look at the number of technology fields of patent citations in a specific technology field. In other words, we examine the wideness of the application of technologies in such a field.

Table 9 shows the classification of innovations in GPT fields using backward and forward citations respectively. Due to the truncation problem of forward citations, on average the numbers of technology fields of citing patents that have cited each technology field are lower than the number of the technology fields of cited patent that the citing patents are based on. Moreover, due to the same problem, the Generality Index *(GI)* of backward citations of each technology field is in general higher than the *GI* based upon the forward citations. However, it has shown that such difference didn't affect the overall classifications results.

By looking at the Generality Indexes, we found that Tech fields 5, 11, 16, 29, 39 and

50 have high values of GI and have wider ranges of citations across all fields in both forward and backward citations, and thus are relatively more generalized than other technology fields. This is also consistent with our finding in Study I and II using patent stocks data across industries. Meanwhile, we also found that Tech fields 9, 38, 41 and 53, especially the latter two have much lower values in terms of GI, which is not consistent with the concept of GPT fields. For these fields, a very high proportion of the citations of these technology fields are from their own fields. A possible reason is that these fields have been surged in the most recent decade and our data only cover the citation activities up to 1995 and might lower the citation activities in such fields. However, we also found that while the GIs are relatively low, these fields have covered a much wider range of sectors in terms of citation activities than others. Therefore, we still include them in the GPT fields. The only difference between the patent stock and patent citation method is the definition of Tech field 50. In summary, we classify ten technology fields as the GPT fields. They are Tech 5, 9, 11, 16, 29, 38, 39, 41, 50 and 53.

[Insert Table 9 about here]

It is shown that 27% of citing patents and 28% of cited patents in our sample are granted to firms in Chemical industry. Therefore, we need to control for the effect of firms from Chemicals industries in our empirical tests. We also found that in most cases, the distributions of citing and cited patents are consistent across all industries. The exception is Pharmaceutical industry, which accounts for 13% patents granted but only 8% patent citations. It might imply that firms from pharmaceutical industries have a relatively higher rate of patenting, but less likely to cite other technologies.

3.2.3 Discussion

The comparison of the measurement of GPT fields using patent and patent citations leads to some interesting discussions in this dissertation study. Three factors have been emphasized in GPT literature (Helpman and Trajtenberg, 1998): “1. they are extremely pervasive and used in many sectors of the economy; 2. they are important and are subject to continuous technical advance; and 3. effective use of these technologies requires complementary investment in the using sector”. Our first measurement of GPTs using patent stocks translates the three characteristics from an innovation “creation” approach. GPTs are pervasively generated by firms from a wide range of industries. Secondly, they are important given that we only focus on those technologies that have been most innovated (the size of the field). However, the cross-firm approach takes less concern about “complementarity” of GPTs. The cross-field citation-based measurement might be able to illustrate the “diffusion” natures of technologies. This is because patent citations provide a record of the link between present invention and previous inventions. They illustrate both the extent to which a particular narrow technology field has been developed (citing and cited patents are from the same technology field), or whether a particular invention is used in a wide variety of application.

There still exists some inconsistency in defining GPTs using the two approaches (Table 10). The knowledge creation approach is superior to knowledge application approach in measuring the “importance”, which is likely to be ignored by the latter. To illustrate, Miscellaneous Metal Products (Tech 14) have found to be pervasively cited by many other fields (48 in backward citations and 51 in forward citations), and have a fairly high value of GI (0.87 and 0.6, both above the mean). However, the overall size of this technology field is only 2.58%, and thus excluded from GPT groups. Another example is

Tech 12 (Pharmaceuticals and Biotechnology). These technologies have been heavily created in the period of study[8]. However, the citation activities in terms of citation generality illustrate a different picture.

[Insert Table10 about here]

However, it is known that using patent data to study innovative activities, especially those of firms is subject to a variety of limitations. It heavily relies on USPTO classification. We only roughly group the technologies into “fields”, but are not able to find out the distances between different technology fields. Because of the availability of patent citation data, our period of study is fairly short and not updated. We have experience a high speed growth in new emerging technology fields, such as biotechnologies and information technologies. Moreover, although we’ve taken into concern the evolution of technology paradigm over year, given time and resource constraint, we could not find out the growth of GPTs (durations or lags of citations). Another difficulty is that patenting in the U.S does not fully reflect improvement in certain industries, such as in software technology. It is because the practice in the USA of protecting software technology through patents is only of recent origin. Also, by using patent data, innovations which could not be easily patented are ignored. For instance, with the aids of GPTs and especially ICTs, firms largely improve their production efficiency and supply chain (distribution) system. The role of GPTs from this aspect deserves further studies. Finally, lack of time serious approach might ignore the distorting impact associated with the changes in the strategic uses of patents that have been observed in some high-tech industries (Bessen and Hunt, 2004; Hall, 2005).

3.3 Geographical distribution of GPTs

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[8] The highly frequent patenting activities might be driven by the nature of pharmaceutical industry.

It is also interesting to look at the comparison of the innovative activities of non-U.S firms in the U.S with that of all firms in the world. Compared with the innovations that are granted to all firms in the world, the patents created by large foreign MNCs (no-U.S firms) account for a much higher proportion of patents granted in USPTO system in Chemical (Industry 4), Pharmaceutical (Industry 5) and Coal and petroleum products (Industry 18), but much lower in Office Equipment (Industry 9), Motor Vehicle (Industry 10) and Aircraft and Other Transport Equipment (Industry 11). According to our early discussion, most of these industries heavily rely on GPTs as their core technologies. Foreign owned subsidiaries are actively innovating and exploring more advanced technologies in industries such as Chemical, Pharmaceuticals and Petroleum in the U.S.

Now we move to the description on firms across all home countries (Table 11). Compared with other countries, Japan, Sweden and Canada account for a relatively higher proportion of firms, but lower proportion of patents and patent citations, while firms from countries like that in Switzerland have largely patented in the U.S. As we have shown in Table 11a, Japan is indeed the second largest innovator in the world, next to the U.S. One possible explanation could be that firms from Japan are less concentrated in knowledge explorative activities, or are likely to remain the innovative activities at home. An alternative explanation is that the subsidiaries of Japanese firms in the U.S are concentrated in less innovative industries.

[Insert Table 11 about here]

Table 11 and Figure 2 show the distribution of GPTs within the U.S. It is illustrated that innovations in GPT fields are most concentrated in technology clusters like CBD 2 (New York, New Jersey and Pennsylvania, etc.), CBD 3 (Michigan and

Illinois area), CBD 7 (Texas area), and CBD 9 (California and Washington). More specifically, we also found that GPTs in the old paradigm such as Chemical Process, Chemical Equipment and General Industrial Equipment are located in the traditional developed area such as CBD 2 and CBD 7 which are based on energy and oil-related technologies, while new ICT-related technologies are mostly to be found in Pacific area (CBD 9).

[Insert Table 12 about here]

[Insert Figure 2 about here]

Chapter 4. GPTs and Corporate Technological Diversification

4.1. Introduction

The first empirical study is focused on defining the core technology fields of an industry, the General Purpose Technology (GPT) fields, the Information and Communication Technology (ICT) fields, and more importantly, investigating how the development of the GPTs and the efforts in developing these technologies contributes to an industry's technological diversification, especially in the new socio-techno-economic paradigm.

General Purpose Technologies (GPTs) are characterized by the "potential for pervasive use in a wide range of sectors and by their technological dynamism" (Bresnahan and Trajtenberg, 1992). Given that these technologies are widely applicable to various research activities, GPTs have been regarded as a "driving force" behind corporate growth, especially behind the technological progress over eras (Granstrand, Patel and Pavitt, 1997; Bresnahan and Trajtenberg, 1995). Given that ICTs bear the same nature as that of GPTs, in the new techno-economic paradigm (Freeman and Perez, 1988; Kodama, 1992; Santangelo, 1998), ICTs are conceived as the advanced GPTs (Hall and Trajtenberg, 2004).

While the profile of a firm's technological diversification has been found to be fairly stable (Rumelt, 1974; Nelson and Winter, 1982), in the new techno-economic paradigm, large firms face an increasing pressure on understanding and building capabilities across a broadening range of technologies. This technological diversification is based on the dynamic economies of scope which are generated in a fundamentally important way through the combination and recombination of various technologies, new as well as old. Given the “pervasive” and “connective” natures, GPTs become the key areas of specialization for firms operating in all industries, especially created by firms which use them to support their primary technologies. These technologies help build the firm’s dynamic capabilities by facilitating the integration and reconfiguration of internal and external competences (Teece et al., 1997). At this point, they are employed as “bridge” and “catalyst” to help fuse the core fields of firms with other technologies and thus believed to increase the degree of corporate technological diversification. Moreover, GPTs, serving as a firm’s core technology fields are believed to play different roles in the diversification process from those staying outside the firm’s core areas.

Based on the U.S patents granted to largest MNCs from 1969-1995, this study suggests that firms increasingly diversify their technology bases by paying more attentions on the technologies outside their core areas. Moreover, in industries in which GPTs are laying in the core technology fields, GPTs are believed to ease the technological diversification to a greater extent. Thus we are expected to observe a higher degree of diversification in GPTs-based firms (in these firms, GPTs are used as primary technologies) than in those industries GPTs are not cores.

GPT related studies are mainly focused on methodology issues and the contributions of GPTs to economy as a whole. Very few studies link these driving force technologies to corporate innovations. Another stream of literature is on the emerging Information and Communication Technologies (ICTs), while ICTs have been studied separately from GPTs (Santangelo, 2002; Cantwell and Santangelo, 2002; Cantwell and Santangelo, 2000). In this research, however, we suggest that ICTs are indeed an advanced type of

GPTs.

Moreover, research on the technological diversification is quite limited. Corporate diversification issue has often been studied from a static approach, focused on the extent of the degree of technological relatedness (Hill and Hoskisson, 1987; Chari, Devaraj and David, 2008) or the management issues in the diversified organizations (Jones and Hill, 1988). This study, instead, tends to study the questions from a dynamic approach, more specifically, investigating the roles of GPTs and ICTs in the corporate technological evolution process.

Furthermore, as distinct from a number of studies that have used patent citations to identify GPTs, which are primarily "field-based" relying on the properties of individual patents (Hall and Trajtenberg, 1995)[9], the technology-industry two-way analysis that we construct in this study allows us to understand GPTs from an "industry-based" and "firm-based" perspective, and so enable us to better capture the nature of technology evolution in an organizational context. In addition, this two-dimensional measurement of a GPT field takes into account concerns over both the "generality" and the "frequency" of GPTs.

This paper is structured in five sections. After giving a general introduction in the first section, we will review previous literature in the corporate technological diversification, GPTs, and the new techno-economic paradigm in section2. In the following section we will build our theoretical model and propose our hypotheses. The fourth section is focused on the data, the construct of variables and the statistical method used in this study. The sixth section is devoted to the analysis of the empirical results and

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[9] In this study, the authors selected 781 patents that have been most cited in the USPTO system from 1975 to 1995., and defined the U.S technology classes of these patents as the General Purpose Technologies.

our main conclusions. Some limitations of this study and the direction of future studies will be discussed in the final section.

4.2. Literature Review

4.2.1 Corporate Technological Diversification

As we have discussed in earlier chapters, to understand a firm's underlying technology trajectory, it becomes crucial to study corporate technological diversification. As new opportunities emerge from general advances in science and technology, firms are on the whole becoming more technologically diversified over time, while the technological competencies of the large firms still depend heavily on the past and are fairly stable (Granstrand et al, 1997). The "path dependency" (Nelson and Winter, 1982) of a firm's technology development is thus linked to the firm's core technologies. Firms beat their competitors by their core products (Prahalad and Hamel, 1990), while the latter are the physical embodiments of one or more core competencies. Rather than emphasizing products and markets, and focusing on competitive analysis on product portfolios, the resource-based view regards the core competences as "a portfolio of technologies". The **core competencies** in our study are therefore defined as a central set of technological capabilities that lead to potentially idiosyncratic strategic growth alternatives.

However, in large firms that are based on "Multi-technology" (Granstrand, et al., 1997; Granstrand, 1998), technological opportunities are increasingly generated in a fundamentally important way through the combination of existing technologies with new ones (Granstrand and Sjolander, 1990). A firm's existing core technologies need to be fused and integrated with new inputs. Therefore, while technological competencies of large firms are fairly stable over time, firms are on the whole becoming more technologically diversified.

Schumpeter (1934) pointed out that innovation takes place by “carrying out new combinations”. Based on this assumption, the linkage between the firm-specific core technologies and firm technological expansion has been proposed by Granstrand and Sjolander (1990). They argued that in “Multi-technology Corporation” (Granstrand, et al., 1997) technological opportunities are increasingly generated in a fundamentally important way through the combination and re-combination of various technologies. These activities lie at the heart of the invention and innovation (Granstrand, 1998).

Corporate technological diversification issue has often been studied from the static approach, such as the firm’s portfolio of businesses/ technologies in terms of a measure of relatedness or divergence (Hill and Hoskisson, 1987; Chari, Devaraj and David, 2008) or the management of the diversified corporations (Jones and Hill, 1988). The dynamic approach is first suggested by Kim and Kogut (1996). They proposed that a firm’s diversification pattern corresponds to a broader so called “technological trajectory” (Nelson and Winter, 1977; 1982; Dosi, 1982) which either derives from acquisition of related knowledge outside of firms or from in-house innovation.

Kim and Kogut (1996) explained the pattern of diversification as linked to firm’s “platform technologies”. More specifically, they proposed that firm’s technological diversification could be derived from the “commonality” or the “complementarity” nature of firm’s knowledge base, and thus there is the distinction between core diversifications and complementary diversifications. At this point, it is interesting to examine how the technological diversification is related to the firm’s core competencies, and moreover, whether there are specific technologies facilitating this diversification process.

4.2.2 GPTs and the New Techno-Economic Paradigm

GPTs

To answer the above questions, we begin with the concept of the General Purpose Technology (GPT). Given their nature of being pervasively and generally utilized, GPTs have been regarded as a "driving force" in economic growth, especially in technological progress over eras (Granstrand, Patel and Pavitt, 1997; Bresnahan and Trajtenberg, 1995).

The concept of technological paradigm (Cantwell and Santangelo, 2006; Freeman and Perez, 1988; Dosi, 1982) has provided a new theoretical framework for innovation studies. Nowadays, a widening range of technological opportunities have derived from Information and Communication Technologies (ICTs) (Granstrand, et al, 1992; Oskarsson, 1993; Patel and Pavitt, 1991), which drives the emergence of a new Techno-Economic paradigm based on the ICTs and related technologies. Compared with the old paradigm which is energy and oil-related technology based, the new paradigm is characterized by the pervasiveness of ever more complex technologies, the increasing importance of science-based technologies (Dosi, 1982; Freeman and Perez, 1988; Cantwell and Fai, 1999), and the fusion of formerly separated technologies (Kodama, 1992). Firms as the main actors in this evolution, tend to reinforce the development of ICTs to support an even more widely dispersed network of differentiated creativity (Cantwell and Santangelo, 2000). Bearing upon some of the more salient characters of the GPTs, in this study we believe that ICTs are an advanced type of GPTs, or we could call them the GPTs in the new paradigm.

These changes have been illustrated in the technological structure of the world's largest MNCs based on patent data. The shares of primary technology (ies) in each industrial group of firms have been tending to decline over time. This implies that a wider range of technologies which lay outside a firm's core areas attract more efforts in corporate innovative activities (Table 13). In other words, firms have tended on average to become more technologically diversified over time.

[Insert Table 13 about here]

4.3. Theoretical Development and Hypotheses

4.3.1 Corporate Technological diversification and Core Technologies

The focus of this study is the determinants of corporate technological diversification, especially the linkage to the development of technologies in GPT fields. It is important to note that **Corporate Technological diversification**[10] (or Technological Diversification) in this study specifically refers the extent to which a firm has technological generation efforts, and not to a diversification in uses or application of technology in production or distribution.

As noted above, given that a firm's diversification needs to be built upon its existing skills or resource base (Rumelt, 1974), this concept is associated with a firm's core competencies (Prahalad and Hamel, 1990). Firm's core competencies are developed from organizational learning, and need to be evolved and changed through continuous organizational learning (Lei, Hitt and Bettis, 1996). Given this nature, among numerous dimensions of constructs to study the "core competencies" (Barton, 1992), we will specifically focus on the knowledge/skills and technology/innovation aspects. A firm's

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[10] Granstrand's (1998) categorize corporate diversification into two fundamental types – business diversification (product and market as special cases) and resource (technology as a special case).

core competences in terms of technology thus trace their roots back to a firm's primary technology (ies) which have been continuously used to build up and reinforce its competitiveness. In this study, we distinguish a firm's core technologies (primary technologies) from other technologies (the technologies outside a firm's primary technological areas) by looking at the technology field (s) which has been created most in a specific industrial group of firms[11].

On the one hand, firms tend to recognize and absorb external knowledge close to their existing knowledge base (Cohen and Levinthal, 1990; March and Simon, 1958). Hence, the search for new knowledge of firms is restricted to a firm's current area of expertise. On the other hand, the specializations on core capabilities are not static but dynamic. Over time, rather than putting all efforts to create their core technologies, firms shift their attentions to develop other technologies. This can be explained by numerous reasons. Firstly, since commercial opportunities emerging from major scientific and technological breakthroughs were rarely clear immediately, large firms need to build up and maintain a broad technology base in order to explore and experiment with new technologies for possible deployment in the future. In other words, firms are motivated to enhance their absorptive capacity (Teece, et al., 1997) to scan and capture technological alternatives which could potentially become their new cores.

Secondly, in large firms which are often viewed as "Multi-Technology Corporation" (Granstrand and Sjolander, 1990), technological opportunities are indeed generated in a fundamentally important way through the combination and recombination of various technologies, new as well as old. Hence, the ever more rapid growth of technological

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[11] The industrial group of firms is classified according to their production outputs。

diversification is explained partially by the exponential growth of the number of combinatorial possibilities and cross-fertilization of different technologies, or the so called 'dynamic economies of scope' (Granstrand, 1998). Furthermore, as we have discussed, the new techno-economic paradigm is characterized by the ever more complex technologies and the more opportunities embodied in an increasing number of technological fields required by firm's principal product field. To catch up the fast technology changes and deliver superior value to customers, firms need to continuously improve and update their principle technologies by linking them to other ones.

Hence, a main driving force behind such diversification is the co-ordination of innovations and changes in a firm's core technological competencies with its complementary ones (Granstrand, Patel and Pavitt, 1997). Gambardella and Torrisi (1996), for instance, found that R&D costs increase more than proportionately to the number of new technological competencies acquired, since the new technologies need to be integrated with other existing competencies in the corporation. Firms thus continuously reinforce their efforts on the specialization of their core technologies, while leave large diversification potentials to the development of complementary technologies and the combination of existing cores with other technologies. In this process, some of the complementary technologies have great potentials to substitute the current cores to become a firm's new core fields. All these discussions lead to our first group of propositions:

4.3.2 The General Purpose Technologies (GPTs) and their "bridging" roles in the technological diversification

Firms extend the range of their technological diversification in a non-random way.

The “path dependency” (Granstrand et al, 1997) of corporate technology development is linked closely to a firm’s core competencies (Nelson and Winter, 1982). Core competencies in terms of technology are typically embedded in one or more technological fields on which firms focus their knowledge search and learning activities, and build their competitive advantages. The latter are defined as the firm’s primary technology field (s) in our study, and they generally follow quite closely the main areas associated with the firm’s industry. It is important to note that technological diversification in this study specifically refers the extent to which a firm has technological innovation efforts, and not to a diversification in uses or application of technology in production or distribution.

Firm’s core competencies are developed from organizational learning, and need to be evolved and changed through continuous organizational learning (Lei, Hitt and Bettis, 1996). As technologies are becoming ever more complex in nature, a broader range of technologies are needed to produce a single product. In order to catch up the fast technology changes and to explore and experiment with new technologies for possible deployment in products with ever broader knowledge base firms have been motivated to continuously improve and update their principle technologies.

In “Multi-technology Corporation” (Granstrand and Oskarsson, 1994), a main driving force behind diversification is the co-ordination of innovations and changes in a firm’s core technological competencies with its complementary ones (Granstrand, Patel and Pavitt, 1997; Granstrand and Sjolander, 1990). In particular, they recognize and absorb external knowledge close to and complementary to their existing knowledge base (Cohen and Levinthal, 1990; March and Simon, 1958). Kim and Kogut (1996) explained the pattern of diversification as linked to a firm's knowledge base when combined with some industry wide "platform technologies". More specifically, the old and new technologies are inter-linked with certain technologies which have generic and complementary natures in the form of GPTs (Arora and Gambardella, 1994; Bresnahan and Trajtenberg, 1995).

GPTs, especially when they lie outside a firm's core fields, facilitate the cross-fertilization of ideas by altering the opportunities for new knowledge creation and new combination of existing, formerly less related knowledge. The development of GPTs not only help improve the core technologies, but work as a "bridge" linking a firm's existing cores to other non-GPT capabilities. This leads to the first set of hypotheses.

As a new techno-socio-economic paradigm derived from the proliferation of the Information and Communication Technologies (ICT) (Granstrand, et al, 1992; Oskarsson, 1993; Patel and Pavitt, 1991) has emerged, a new institutional set-up of the economy has been observed. It is characterized by the pervasiveness of ever more complex technologies, the increasing importance of science-based technologies (Dosi, 1982; Freeman and Perez, 1988; Cantwell and Fai, 1999; Cantwell and Santangelo, 2000), and the fusion of formerly separated technologies (Kodama, 1992).

Increasing product specialization also leads to a process of knowledge accumulation in the sense that companies cumulate expertise in non-core technological fields (Granstrand, et al., 1997; Patel and Pavitt, 1997). At this point, the development of GPTs will not be constrained to their own industries, but widely spread across a variety of industries. The growth of GPTs is thus primarily attributed to the creation of these technologies by firms which are using GPTs to complement their primary technologies.

In other words, of the growing development of the GPTs across all industries, firms which create these technologies as their complementary technologies tend to account for an increasing proportion. This is also the case of ICTs.

Therefore, firms as the main actors have been motivated to build up and maintain an ever broader technology base in order to explore and experiment with new technologies for possible deployment in products in the future. These reasons along with the fact that ICTs are most generalized compared with other technologies (Hall and Trajtenberg's, 2004), ICTs are conceived as a 'carrier branch' of the new paradigm (Freeman and Perez, 1988), or as the 'catalyst' of the fusion of formerly separate technologies (Kodama, 1992). Therefore, firms in the new paradigm attempt to further reinforce the development of ICTs to support an even more widely dispersed network of differentiated creativity (Cantwell and Santangelo, 2000). A very compelling example is that a wide range of industries covering aircraft or other transportation equipment, construction, printing, petroleum and pharmaceuticals are now using CAD (computer-aid-design) and other information-related technologies to help design products or improve the processing system.

Hypothesis1a: Firms in industries outside that for which a given GPT is primary technology account for a rising proportion of development in that GPT field.

Hypothesis1b*:* Firms in industries outside that for which a given ICT is primary technology account for a rising proportion of development in that ICT field.

Hypothesis2a: Firms in industries in which the primary technology are non-GPTs, GPT fields account for a rising share of total development outside their respective primary field (s).

Hypothesis 2b: Firms in industries in which the primary technology are non-ICTs, ICT fields account for a rising share of total development outside their respective primary field (s).

Moreover, technology management literature, the absorptive capacity in terms of the firm's dynamic capability is deemed as how a firm integrates, builds and reconfigures internal and external competences (Teece, et al., 1997). The development of GPTs and ICTs will enhance firm absorptive capacity by improving their ability to identify and assimilate external knowledge and keep firms abreast of latest development (Cohen and Levinthal, 1989; Tilton, 1971). The GPTs are thus playing the role of 'enabling technologies', opening up new opportunities rather than offering complete, final solutions. Experience in these technologies will serve as a 'platform' for further sectoral expansion (Kim and Kogut, 1996).

At this point, the GPTs and ICTs play a great role as core areas of expertise enabling firms to exploit the potential of the convergence between formerly separate sectors of competencies. The mastering of such core technologies provides firms with flexibility in the combination and fusion of previously separate branches of technologies. Therefore, when GPTs and ICTs are the core technologies, the combination and re-combination of various technologies will be further facilitated, while when GPTs and ICTs are non-core in the industries, firm's core technologies are less likely to be fused with other technologies given that there is lack of GPT and ICTs as "bridge" between them. Consequently, we propose that when firm's core technologies are GPTs and ICTs, firms are less likely to be concentrated on their cores. In other words, firms tend to have higher degree of technological diversification. We also expect that compared with GPTs, ICTs have a greater potential to enable the combination/recombination of a firm's primary technologies with other ones, and thus tend to lead to a greater degree of technological diversification of firms.

Hypothesis3a: Firms in industries for which the primary technologies include GPT fields tend to have a higher degree of technology diversification compared to firms from other industries.

Hypothesis3b: Firms in industries for which the primary technologies include ICT fields tend to have a higher degree of technology diversification compared to firms from other industries.

Based on above discussions, the research model of this study is shown in Figure 3.

[Insert Figure 3 about here]

4.4. Data and Methodology:

4.4.1 Data

This study is based on the patent stocks that are granted to the largest industrial firms in USPTO system. The U.S patent data in this study cover patents granted to largest MNCs in the U.S from year 1965 to year 1995. The 948, 190 patents are organized as a panel dataset indexed by the period they are generated, the MNC group the patents belong to and the technology field the patents are assigned to respectively.

As we have discussed in Chapter 3, patents in our dataset are belong to one of 16 industries on the basis of its primary field of production (Cantwell and Andersen, 1996) and are allocated to one the 56 technological fields (Cantwell and Andersen, 1996). Again, the use of the term "technology (ies)" or "technology field (s)" referring to one of the 56 technology fields, and the term “industry” or “industrial group of firms”, referring to groups of firms are differentiated. The 56 technological fields and 16 industries are listed in Table 3 and Table 4 respectively.

[Insert Table 3 and Table 4 about here]

4.4.2 Independent Variables and Dependent Variables

GPT fields

We employ the cross-industry technology creation approach to measure GPTs in this study. We identified nine fields as GPT fields, and among them, office equipment (tech 41) and other instrument and controls (tech 53) have higher growth rates compared with the other 7 technological fieldss. These two technology fields are literally ICTs, which are also consistent with the theoretical definition in previous discussion and other literature (Santangelo, 1998; Cantwell and Santangelo, 2000), that they are conceived as the GPTs in the new techno-economic paradigm (ICTs). By contrast, the other 7 technologies are viewed as GPTs in the old paradigm given that their growth rate is either negative or lower.

[Insert Table 6 and Table 7 about here]

The Primary Technology Field (s)

According to our definition, a firm’s primary technology fields are those that are “primary” to the industry which the firm belongs to. Hence, we assume that firms in the same industrial group tend to share the same primary technological field (s). We proxy the allocation of these fields by comparing the shares of technologies created in each industry, based on the table which shows the share of industries in each technology field *(Ind_Tech)*. Allowing for the fact that the share of industries within each technological field might overstate the primary fields of larger industries but understate those of smaller industries, we further calculate the RTA index[12] from each *Ind_Tech* share to show the relative degree of concentration of industries in each technological field. The RTA index of each technological field across 16 industries is:

$$RTA_{ij} = (P_{ij} / \sum_i P_{ij}) / (\sum_j P_{ij} / \sum_{ij} P_{ij})$$

Again, here *Pij* denotes the number of patents granted in industry *i* and technological field *j*. The value of RTA varies around unity. Higher RTA values indicate that a technology field is comparatively a focus of attention in that industry in relation to other fields, while lower values imply areas of development that are less important for an industry.

For each technological field, to decide in which industry it is utilized as the primary technology field, we follow the rule that: firstly, the industry should have either the highest absolute value of *Ind_Tech* share (>55%) or the highest absolute value of RTA (>8) in the field; secondly, the rest fields' primarily utilized industry is selected according to the relative highest RTA; moreover, for industries 4, 6 and 8, which have relatively large industry sizes but their innovative activities are dispersed across a wide range of technological fields, the primary technology field(s) will by decided by largest *Ind_Tech* share. Thus as shown in Table 13, each technology field is allocated to one industry as the main industry it serves, and for each industry, there is at least one (one or more than one) primary technology field (s). The allocation of the primary technologies shown in this table are consistent with conventional expectations on the categorization in literature (Cantwell and Andersen, 1996).

[12] Revealed Technological Advantage (RTA) index (Cantwell, 1989)

[Insert Table 13 about here]

It is important to note that in this study, GPT fields and the core technology fields are two separate and independent dimensions in classifying technologies. Any technologies which belong to GPT fields could be core or non-core technologies to a firm. To illustrate, the computing technologies belong to GPTs and are core technologies for IT firms such as Microsoft and Google, but they are peripheral technologies for firms in other industries such as Boeing (aircraft), Toyota (automobile) and Roche (pharmaceutical). Firms as Microsoft and Google are GPT-based, while other firms such as Boeing, Toyota and Roche are non-GPT based, but the latter also create GPTs to support their core competency creation.

	Cores	**Non-cores**
GPTs	• Electrical technology in GE • Machinery technology in Caterpillar	• Electrical technology in Boeing • Machinery technology in Kraft
Non-GPTs	• Aircraft technology in Boeing • Food -related technology in Kraft	• Power plant technology in Boeing • Image and sound equipment in GE

Dependent Variables

The degree of technological diversification

Corporate technological diversification studies often used SIC-based measurement (Bass, Cattin and Wittink, 1978), the categorization measurement (Remelt, 1974, 1977, 1978), or product diversification measurement to proxy the degree of diversification. In this study, the diversification degree is measured two ways. The proxy for the technological diversification of subunits is based on the consideration that technological diversification is inversely related to the extent of the concentration of the firm's technological specialization. Therefore, we first use the change on the share of the primary fields to measure the technological diversification.

We complement the above measurement by adopting a similar measurement as to the Entropy measure in Zander (1999)'s study for the degree of technological diversification. It is measured by and the inverse of the coefficient of variation (*CV*) of the shares of patents across all the relevant sectors for the industry-country group. Therefore, in each period considered, the proxies for the SUB TECH DIVE are the reciprocals of the *CV*s, in particular:

$$CV_{tech\_Ind} = \sigma_{tech\_Ind} / \mu_{tech\_Ind} = \sigma_{P_{ij}/\sum_j P_{ij}} / \mu_{P_{ij}/\sum_j P_{ij}}$$

Where *Pkj* denotes the number of patents granted in MNC group *k* and technological field *j*. *Psj* denotes the number of patents granted in subunit *s* and technological field *j*. It is noteworthy that the CV is captured by disaggregating the 30 years in our patent data into three periods. Therefore, the degree of concentration of the *Tech_Ind* shares varies over time.

4.5. Empirical Findings and Conclusions

4.5.1 Statistical Descriptions

Industry shares and their primary lines of technological effort reflect a boom in the ICT-based business sectors. Over all three periods in study, Office equipment industry which is primarily based on office equipment technology, professional and scientific instruments industry which mainly relies on other instruments and controls are the fast growing ICT areas. In addition, we also observed an increase in shares of Electrical Equipment industry and Paper products, Printing and Publishing industry. Although these two industries are not ICT industries, their innovative activities are closely linked to the

R&D of ICT fields, such as in printing and publishing sectors which once were heavily reliant upon printing and publishing machinery but have now become more computer and Internet technology driven.

When we look at the technology field distribution in each industrial group of firms in Table 13, we find that in average, the shares of firm's primary technology activities are decreasing over time. Based on the presumption which we have discussed in previous sections, that is, the more the share of industry's primary technology field, the less diversified the industry's technological pattern, it suggests that most industrial groups tend to become less concentrated on their core technologies over time.

[Insert Table 13 about here]

Now with this technical field/industry combination, we are able to analyze the geographic distribution of each technology field across different industries, and the geographic allocation of various technologies within the same industry. Our unit of analysis is the share of technologies used in each industrial group of firms over three periods. Panel regression techniques are utilized in this study to investigate dynamic aspects with respect to the hypotheses about the distribution of GPTs and ICTs across industry (group of firms) boundaries.

4.5.2 Regression results and conclusions

The correlations of all variables listed in Table 14 show that there is no major multicollinarility problems in our models. Given that the shares of 56 technology fields in the industrial groups of firms and the shares of industrial groups in the technology fields and the share of the primary technologies are normally distributed, when testing the linkage between the change of technology structure and the geographical re-allocation of innovative activities, we will mainly use OLS regressions.

[Insert Table 14 about here]

We first use the share of primary technology fields in each industry as the dependent variable. The regression results are shown in Table 15. Model 1 is the baseline test. It shows that controlling for the size of the industry, the industry and period, the negative coefficient in the GPT-based industry implies that the shares of a firm's primary technologies in these two types of industries tend to be lower compared with other industries. However, we didn't find consistent result for that of the ICT-based industries.

[Insert Table 15 about here]

Model 2 and Model 3 are focused on the relationship between the development of a firm's primary technologies and the innovations in GPT and ICT fields. The result shows that compared with other technologies, the extent of development of GPTs in a given industry tends to be positively correlated to the share of the firm's primary technologies. Model 3 showed a similar result, by illustrating that the innovations in both GPT and ICT fields in a certain industry, especially in the latter are positively associated with the share of primary technologies in the industry. This finding is further supported by the results in Model 4 and Model 5. We do find a positive relationship between GPT developments as they are laying in the non-primary fields in an industry, however, the result is not significant. Since we assume that firms in the same industrial group share the same primary technology fields, and thus the share of primary technology fields is negatively associated with the degree of technological diversification of that industrial group. The results show a negative relationship between GPT and ICT development of a given industry and the technological diversification of that industry, even these technologies are created as the supporting technologies. Such findings don't support our hypotheses on the role of GPTs in corporate technological diversification. This is probably because the dynamic nature of old-paradigm GPTs has been weakened as compared with the new-pardigm GPTs – ICTs.

We take robustness tests by replacing the share of primary technology fields in an industry with the IND_DIV of that industry (Table 16). As we discussed earlier, the IND_DIV is calculated as the dispersion of distribution of technology generation in each industry. We obtained some different results in the second set of analysis, and it is worthy to compare the two sets of results. Firstly, Model 6 shows that while GPT-based firms are likely to be more technologically diversified than firms from other industries, ICT-based firms are more technologically specialized. This result partially supports our hypothesis. The reason of a negative effect as ICTs lie in the primary technology field in an industry as to the technological diversification is probably explained by the fact that ICT and related technologies are newly emerged only in most recent time, firms in such industries might not be mature enough to diversify their technological profile.

[Insert Table 16 about here]

Again, regressions in Model 7 and Model 8 are taken to find out the role of GPTs as to the overall technological diversification of the industry. We do find that in general, firms in which the extent of development in ICT fields is higher tend to have a higher degree of technological diversification, but it doesn't stand for development in GPT fields. This finding seems contradicted with the conclusion that we drawn from Model 5 - ICT-based industries are relatively less diversified. Regression results in Model 9 and Model 10 further explain this issue by suggesting that ICT development supports an industrial's technological diversification is because these technologies lie outside an industry group's primary fields. In other words, ICTs are working as the "connector" only when such technologies are developed to support the core areas.

Based on above discussions, we suggest that GPTs are increasingly generated as the technologies outside the firm's core areas, to support the innovations of the firm's principle competencies. Given their "pervasive" and "connective" nature and the high degree of "complementarity", the efforts on ICTs are believed to help enhance firm absorptive capacity by combining the firm's core technologies with external inputs and consequently lead to technological diversification. Firms are thus able to scan and capture new technological alternatives which are potentially their new cores. At this point, firms in industries in which the core technologies are ICTs, tend to have a higher degree of technological diversification compared with firms in other industries, and this is also true in ICT-based firms.

Chapter 5. GPTs and the International Innovation Networks of Multinational Corporations

5.1. Introduction

As we concluded from study I that the combination and re-combination process which explains most technological diversifications nowadays are eased by the **General Purpose Technology** (GPT) (Helpman and Trajtenberg, 1998). GPTs are the technological fields in which innovations are widely generated in many industries, and lead to continuous technical advance. In the new paradigm, GPTs (ICTs) facilitate the connection of a firm’s technologies in core areas with new knowledge inputs sourced from external networks.

In this chapter, we further investigate the role of GPTs in the internationalization process of corporate innovative activities. As new growth opportunities became associated with the internationalization of advanced technological capabilities (Vernon, 1979; Kogut, 1989, 1990; Pearce and Singh, 1992; Cantwell and Janne, 1999), organizational and geographical boundaries may not encompass entirely the generation of new technologies. Since the technology profile of each location is historically bounded and is characterized by some specific path of specialization over time (Dosi, Teece and Winter, 1992), foreign subsidiaries in multinational corporations (MNCs) have some ever more distinct technological profiles compared with that of the headquarters, and thus become the sources of new ideas and capabilities for the corporate groups (Pearce, 1989; Cantwell, 1992, 1995; Birkinshaw and Morrison, 1995; Cantwell and Mudambi, 2005).

The new capabilities are synthesized by large firms with a globally rationalized network (Hedlund, 1986; Porter, 1986; Bartlett and Ghoshal, 1989). This cross-border integration allows firms to create firm-specific advantages by transferring knowledge within the geographically dispersed networks (Gupta and Govindrajan, 2000; Hansen and Lovas, 2004; Almeida, 1996). This stream of literature is in turn linked to the recent contributions on the beneficial effects of the continuous combining and re-combining of technologies within international network. More specifically, the ability to combine and re-combine technology on an international scale has become particularly important for MNCs, which appears to be one of the advantages of “multinationality”.

In this context, GPTs and more recently ICTs are believed to make feasible the combination and recombination of a firm’s existing technologies in the core areas with new external knowledge inputs on an international scale. They help fuse the existing knowledge originated from parent firms with new ones sourced in foreign locations. At this point, the specialization on innovative activities in GPT fields as a means of bridging to the firm’s core fields of innovations appears to be one of the advantages of “multinationality”.

This study is based upon the same set of data which cover U.S patents granted to the world’s largest industrial firms from 1969 to 1995. To the dynamism of the sectoral diversification and geographical expansion of the technological profiles of multinational corporations, we further classify the patents according to the country of origin of the MNC group they belong to, as well as the location of the actual innovation. The latter is perceived as host country in our study. The analysis of GPTs and a firm’s core technologies in the context of its industry is fitted into the context of the restructuring of a multinational firm's internationally integrated innovation network. We empirically investigate the GPT development across the MNC's geographically distant subunits to examine whether and if so how, it is connected to the change of the pattern of corporate competence-creation activities. The research framework is shown in Figure 4.

[Insert Figure 4 about here]

Our empirical findings suggest that while in general GPTs, when they constitute a firm's primary technologies, are very likely to remain at home in the parent company of MNCs, given their "pervasive" and "enforcing" nature, when these technologies lay outside a firm's primary technology areas, the geographical distribution of creative efforts in these fields tends to be locationally dispersed instead. Moreover, the internationalization of a MNC's innovation activities in the GPT fields is proposed to be positively related to the geographical dispersion of the overall technological profile of the MNC, but only when these GPT-related technologies are invented as supporting capabilities. More recently, this dispersion is accompanied with a geographical re-allocation of a firm's core innovative efforts away from the home country. In particular, there is a positive relationship between the competency-creating activities in a firm's core technology fields in selected foreign subsidiaries and local specializations of GPT fields in such subsidiaries. This is because firms develop technologies in the GPT fields at subsidiary level to facilitate the combination of their existing competencies with new inputs sourced in foreign countries. The new combinations tend to become the growth alternatives to diversify the technological profiles of firms in a global scale.

This chapter is structured in five sections. Following a general introduction in this section, we review the most relevant literature on the internationalization of corporate technological activities and the MNC international innovation networks in section 2. The following section discusses two broad topics: 1. the internationalization of innovations in primary technology fields and GPT fields, and 2. the role of GPTs to the restructuring of international innovation networks of MNCs. The above discussions lead to theoretical development and hypotheses. The fourth section is devoted to the data, constructs of variables and the statistical methodology. The fifth section discusses the empirical results and tests of robustness. Some conclusions, practical implications of this study and the direction of future studies are mentioned in the last section.

5.2 Literature Review and Theoretical Background

5.2.1 Technological Diversification of Multinational Corporations

Firms grow by exploiting existing competencies, and thus tend to maintain their coherence (Teece, et al, 1994) by generating and exploring synergies of various types of resources and competencies (Schumpeter, 1934). In the "Multi-technology Corporation" (Granstrand, et al., 1997; Granstrand, 1998), technological opportunities are increasingly generated through the combination of existing technologies with new ones (Granstrand and Sjolander, 1990). These combination and re-combination activities largely explain the pattern of corporate technological diversifications (Kim and Kogut, 1996).

Corporate technological diversification is conventionally understood as being unrelated or negatively related to the internationalization. Diversification is mainly the domain of R&D in parent organizations located in the home country, before being transferred to other parts of the corporate group (Vernon, 1966). From the mid-1980s, an apparent trend toward internationalization of the R&D function have lead greater attention to be paid to the role of foreign subsidiaries as an increasingly important source of new ideas and capabilities (Bartlett and Ghoshal, 1989; Hedlund, 1986; Cantwell, 1992, 1995; Hakanson and Nobel, 1993; Zander, 1997).

For growth alternatives, instead of just utilizing capabilities already in hand, contemporary MNCs use their international operations to develop new capabilities in areas that were not previously among the fields of specialization of their parent company (Dunning and Narula, 1995; Pearce and Singh, 1992). They create local centers of excellence targeted at differentiated but complementary sources of expertise that match those of the host countries in which they are located (Cantwell and Janne, 1999; Kuemmerle, 1997; Zander, 1998). This is supported by the evidence that countries are becoming more technologically specialized and differentiated one another over time (Archibugi and Pianta, 1992), and thus national and regional innovation systems are characterized by specific technological expertise into which MNCs from around the world can tap (Cantwell, 1993, 1995, 2000).

5.2.2 Technology Accumulation of MNCs with the International Innovation Networks

To protect the competencies and to avoid competing directly with the stronger international players in their primary fields (Cantwell and Santangelo, 1999; Cantwell and Kosmopoulou, 2002), the internationalization of innovative activities is limited to only a few fields of a firm's non-core areas (Cantwell, 2000, Zander, 1997). More recently, this pattern has been changed. More recently, greater attentions have been paid to the role of foreign subsidiaries as active innovators (Hakanson and Nobel, 1993; Zander, 1997).

While in general the share of patents accounted for the core technology (ies) in each industry group tends to decline over time, the share of innovation activities of core technologies in each industrial group which is associated with innovative activities outside of the countries of origin has risen over time. This implies that MNCs have re-allocated increasingly more R&D activities in the core fields outside their home countries to at least some foreign subsidiaries. These subsidiaries play as a bridgehead between external and internal innovation networks of a MNC, and thus become strategically more important for the MNC than others. This is consistent with literature that while some units may be designated as “product mandate” (exploitation) subsidiaries, some others become part of a larger innovative effort across the world (with “world mandate”) and even members of the core development group in ‘global innovation projects’ (Hudlund and Ridderstrale, 1995).

The reduction of spatial barriers and the dynamic economies of scope (Teece, 1997) are one of the important features of techno-economic paradigm change. These trends are reflected in the interaction between more geographically dispersed innovation networks and the development of a wider range of diversified technologies within MNCs.

The argument of internationally diversified R&D activities is further supported by the findings which have spoken of a shift amongst multinationals away from systems of independent locally oriented affiliates towards a globally rationalized network (Hedlund, 1986; Porter, 1986; Bartlett and Ghoshal, 1989). Such a re-structuring encourages a higher degree of involvement of foreign subsidiaries in the competency-augment activities, and helps minimize the “duplication of effort” issues (Hakanson and Zander, 1988). In this context, instead of exploring more deeply the existing capabilities, MNCs may reallocate the R&D efforts to foreign countries which have differentiated but complementary sources of expertise that match those of the host countries in which they are located.

5.3. Theoretical Development and Hypotheses

5.3.1 The Internationalization of GPTs and Other Technologies

Technologies are becoming ever more complex in nature, and the creation of new technologies is driven by the combination and recombination of existing technologies. Firms extend the range of their technological diversification in a non-random way. The old technologies and new ones as a rule either share a common knowledge base or common scientific principles (Breschi, Lissoni and Malerba, 2003), or they become inter-linked with certain technologies which have generic and complementary natures in the form of GPTs (Arora and Gambardella, 1994; Bresnahan and Trajtenberg, 1995). Therefore:

Hypothesis 1: *Technologies in GPT fields that are created in foreign countries of MNCs are more likely to be created as non-primary fields of technological development than as primary fields across firms of different industries.*

The changing pattern of the international technological networks of MNCs is not only influenced by location-specific factors (locational economies), but also by a set of firm-specific and technology-specific characteristics. When targeting a location for the purpose of setting research efforts, firms need to explore the technological expertise that foreign subsidiaries can take from the host environment in which they operate, and take account of the varying degree of the centrality of such technologies in their own specific innovation network (Dosi, 1988). To avoid competing directly with the stronger international players in the location of activities in their primary fields (Cantwell and

Santangelo, 1999; Cantwell and Kosmopoulou, 2002), the most important technologies in large firms are still generally maintained in the home country (Cantwell, 2000, Zander, 1997). In order to complement these primary technologies, the development of which has been relatively confined at home, increasingly more advanced and substantial technological capabilities in other supporting fields have been generated outside the countries of origin (i.e. Zander, 1997).

Another factor that affects the extent of the locational concentration or dispersion of innovative activities is the degree of complexity embedded in certain technologies (Cantwell and Janne, 1999). Some kinds of technologies are geographically more easily dispersed while the cross-border learning and transfer of some others are much more difficult due to their more tacit natures. GPTs are often an example of the latter, usually being science-based in character. Technological progress involves a combination of proprietary and public sources of knowledge (Cohen and Levinthal, 1990; Dosi, 1988). Science-based technology is characterized by the combination of a more intense usage of public and codified knowledge with more knowledge as well of a proprietary nature which is so called ‘tacit knowledge’ (Nelson, 1992). Given that tacit knowledge is specific to organizations as well as geographic locations, to some extent, the external accessibility to this knowledge will be impeded. So the development of GPTs involves more organizational learning and tends to be more geographically localized. Furthermore, in the new techno-economic paradigm, new distant-shrinking technologies are unlikely to undermine the value of proximity because the diffusion of codified knowledge amplifies rather than devalues the significance of tacit knowledge (Nooteboom, 1999). This is the reason why geographical proximity is more important for the emerging biotech industry which is mainly based upon gene science than the established industries such as the traditional chemical industry (Mariani, 2004).

However, in the new techno-economic paradigm, firms under the pressure of the ever more complex combinations required by cutting-edge technologies and the uncertainty associated with high R&D costs, need to cumulate expertise in technological fields beyond their primary areas (Granstrand et al., 1997; Patel and Pavitt, 1997) for the generation of more complex products and production processes. Many secondary technologies lie in the GPT fields. In this case, the creation of the highly tacit knowledge needed in most development in the GPT fields is likely to be accessed most readily in locations that are specialized in these same fields. Thus, it is also likely that MNC efforts in these fields will be localized within foreign subsidiaries which have been sited in the relevant locations or centers. This process is driven both by particularly strong and unique local competencies within locations and by particularly strong company-specific networking capabilities in an innovative MNC (Cantwell and Santangelo, 1999; Bartlett and Ghoshal, 1989, 1990; Cantwell, 1992). In summary, when firms are primarily specialized in technologies other than GPTs, foreign facilities in their MNC network are more likely to take the role of developing such technologies. Thus, we contend the following hypotheses:

Hypothesis 2*: Compared with innovative activities in non-GPT fields which serve as the primary areas of technological development for a firm's industry, innovation activities in GPT fields when they lie in a firm's primary areas are more likely to remain at home.*

Hypothesis 3a: *When GPT fields lie in non-primary fields for a firm's industry,* *technology innovations in these fields are more likely to be located in foreign countries compared with other non-GPT non-primary technological efforts.*

Hypothesis 3b: *When GPT fields are non-primary for a firm's industry, technology creation in these fields is more likely to be dispersed across many countries compared with other secondary areas of technological effort.*

5.3.2 GPTs and technological diversification of corporate innovative activities

As we concluded from the earlier chapter, in "Multi-technology Corporation" (Granstrand and Oskarsson, 1994), a main driving force behind diversification is the co-ordination of innovations and changes in a firm's core technological competencies with its complementary ones (Granstrand, Patel and Pavitt, 1997; Granstrand and Sjolander, 1990). In particular, they recognize and absorb external knowledge close to and complementary to their existing knowledge base (Cohen and Levinthal, 1990; March and Simon, 1958). Kim and Kogut (1996) explained the pattern of diversification as linked to a firm's knowledge base when combined with some industry wide "platform technologies".

More specifically, the old and new technologies are inter-linked with certain technologies which have generic and complementary natures in the form of GPTs (Arora and Gambardella, 1994; Bresnahan and Trajtenberg, 1995). GPTs, especially when they lie outside a firm's core fields, facilitate the cross-fertilization of ideas by altering the opportunities for new knowledge creation and new combination of existing, formerly less related knowledge. The development of GPTs not only help improve the core technologies, but work as a "bridge" linking a firm's existing cores to other non-GPT capabilities. This leads to the first set of hypotheses.

Hypothesis 4a: *There is a positive relationship between the extent of development of GPTs and the degree of technological diversification of the industry-country group.*

Hypothesis 4b: *There is a positive relationship between the extent of development of GPTs when they lie outside the core fields and the degree of technological diversification of the industry-country group.*

5.3.3 GPTs and the internationalization of MNC innovative activities

The reduction of spatial barriers and the dynamic economies of scope (Teece, 1997) are some of the important features of the technology paradigm change. These trends are reflected in the interaction between more geographically dispersed R&D facilities and the development of a wider range of diversified technologies within MNCs.

Foreign subsidiaries within a MNC differ in terms of context, capabilities and organizational roles, and consequently differentially exposed to new knowledge, ideas and opportunities (McEvily and Zaheer, 1999). Compared with R&D activities in MNC headquarters, those occurred in the foreign units are associated with a significantly higher probability of entry into new and more distantly related fields of technology, creating a long-term drift into new competencies (Zander, 1998). In order to complement principle technologies which have used to be confined at home, increasingly more advanced and substantial technological capabilities are generated outside the countries of origin (Zander, 1997). Because R&D in foreign locations may be able to transcend the limitations in the technological specializations of their home country and take advantage of different specializations abroad, some firms are able to take competitive advantages compared with others, as the breath and variety of the network resources are increased (Malnight, 1996).

In this context, some subsidiaries are becoming active contributors to an MNC's global innovation network. As we observed, an increasing proportion of technologies lying in the primary fields tend to be found in some MNC foreign subunits. These subsidiaries play the role of a bridgehead between local external and cross-border internal units of an MNC, and thus become more important for the MNC than others. The new ideas and opportunities are able to be embraced by MNC groups through an ever more closely integrated international network (Hedlund, 1986; Bartlett and Ghoshal, 1989).

Diversification based on knowledge complementarity (Arora and Gambardella, 1994; Bresnahan and Trajtenberg, 1995) and combination is closely linked with the critical roles of GPTs. We argue that an increasing corporate specialization in GPT fields nowadays by raising combination capability will lead to a growing internationalization of corporate R&D over time, including efforts in some technological fields which lay in the firm's core areas. The re-structuring and integration of MNC international technological networks comes not only from that each affiliate specializes in accordance with the specific characteristics of local production conditions or market requirement (Cantwell, 1995), but because these aspects of greater locational specialization are complementary to a firm's existing primary technologies, and so may be potentially combined with the latter. Since GPTs are very "connective" in nature, they facilitate the combination of core technologies sourced from parent firms and other subsidiaries with external inputs drawn from local firms and organizations. Therefore, a technological specialization in GPT fields tends to enhance the capabilities of firms to maintain a more integrated cross-border innovation network. Foreign subsidiaries may thus become the "bridge" between headquarters and other units in host countries.

Hypothesis 5a: *There is a positive relationship between the extent of technology development in GPT fields and the degree of geographical dispersion of the country-industry group.*

Hypothesis 5b: *There is a positive relationship between the extent of development in GPT fields which lie outside the primary areas for a firm's industry, and the degree of internationalization of the innovations in that country-industry group.*

5.3.4 GPTs and the restructuring of MNC international innovation networks

The shift of innovative activities towards foreign affiliates is closely linked to the evolution of MNC international innovation networks. Previous literature has suggested that a firm's core technologies are still generally remained in the home country (Cantwell, 2000, Zander, 1997). However, nowadays firms under the pressure of the ever more complex combinations required by cutting-edge technologies and the uncertainty associated with high R&D costs, need to accelerate the knowledge accumulation process in technological fields beyond their primary areas (Granstrand et al., 1997; Patel and Pavitt, 1997), and combine them with the existing ones for generating more complex products and production processes. This knowledge integration is not limited to be completed in the home countries. Instead, multinational firms tend to choose the optimal place to complete the "synthesis" process.

The "commonality" and "complementarity" natures of knowledge generation mechanism make the re-structuring of MNC innovation system feasible. In particular, the old technologies and the new ones either share a common knowledge base or common scientific principles (Breschi, Lissoni and Malerba, 2003), or inter-linked with certain technologies with generic and complementary natures (Arora and Gambardella, 1994;

Bresnahan and Trajtenberg, 1995).

On the one hand, knowledge transfer in a firm's primary areas is mainly based on the "commonality" nature. Although outsourcing is becoming increasingly important nowadays, the innovation activities in a firm's core areas are still constrained by organizational boundaries, that is, through the intra-firm innovation networks. Another reason is that intra-organization mechanism is faster and more effective than inter-organization (Granstrand, 1998) channels and are superior in knowledge transfer (Kogut & Zander, 1993). On the other hand, the firm's existing core technologies need to be extended and combined within new inputs that are sourced from host countries and are technologically distant from existing ones. This combination process is explained by the complementarity nature of technological generation (Arora and Gambardella, 1994; Bresnahan and Trajtenberg, 1995).

In early stage of MNCs, the integration process is likely to be completed in the home countries. More recently, given the shorter product life cycle and the increasing complexities of technologies, such combinations are likely to be completed in the most suitable locations within MNC innovation networks where new technology expertise is more easily to be accessed and acquired. The following combination and recombination process is in need of technologies in GPT fields. In this case, the creation needed in most development in the GPT fields is likely to be accessed most readily in locations that are specialized in these same fields. Thus, it is likely that MNC efforts in GPT fields will be localized within foreign subsidiaries sited in specific countries or regions in which MNCs are able to explore technological specializations for their growth purpose. Certain foreign subsidiaries are thus the "bridgehead" linking parent firms and the external innovation networks in foreign countries.

The re-structuring of MNC international technological network is not only because each affiliate specializes in accordance with the specific characteristics of local production conditions or market requirement (Cantwell, 1995), but because these locational specializations are complementary to the firm existing core technologies. The combination of new technology expertise with current ones helps firms diversify their technological portfolios.

In summary, rather than maintaining all innovation activities in core technology fields at home, large multinationals are increasingly re-allocating the development of cores abroad. Meanwhile, since the integration and combination of new and old technologies require the involvement of GPTs, the geographical dispersion of a firm's core technologies tends to be accompanied by the development of GPTs in at least some foreign R&D facilities. These specific innovation facilities are considered a MNC's competence-augment subsidiaries (Cantwell and Mudambi, 2005) or centers of excellence (Cantwell and Janne, 1999; Kuemmerle, 1997). The empirical model is shown in Figure 4.

Hypothesis 6a: *There is a positive relationship between the extent of development of GPTs and the extent of development of core technologies in that industry-country-host group.*

Hypothesis 6b: *There is a positive relationship between the extent of development of GPTs when they lie outside the core fields and the extent of development of core technologies in that industry-country-host group.*

Hypothesis 7a: *There is a positive relationship between the extent of development of*

GPTs and the degree of technological diversification in that industry-country-host group.

Hypothesis 7b: *There is a positive relationship between the extent of development of GPTs when they lie outside the core fields and the degree of technological diversification in that industry-country-host group.*

[Insert Figure 4 about here]

5.4. Data and methodology

5.4.1 Data

This study is investigating the innovation activities of large multinational firms based on the same USPTO patent dataset. We extend the dataset by adding the locations of innovative activities. In other words, we are interested in the geographical structure of MNC innovation networks and its change over time. The dataset covers patents granted in the U.S from 1969 to 1995, which are further divided into three periods of nine year each. The data are organized as a panel of patents indexed by the period they are generated, the MNC group to which the patents belong, the industry to which the MNC belongs, the technology field the patents are in, and the countries of origin in which the patented technologies have been originally invented. The data include patents of 308 largest multinational manufacturers that are originated from 26 home countries and have foreign innovative activities in 58 host countries.

Table 11 illustrates the geographical pattern of technological innovations in GPT fields across different home countries from 1969 to 1995. It is shown that U.S and Japan have been most innovative compare with other industrial countries. These two countries together account for a large majority of all patents granted in the period of study. The foreign R&D activities of firms from these two countries, however, have a much lower proportion. Especially in the case of Japan, there are only about 3.6% innovations from their subsidiaries in foreign countries.

However the distribution of the creations of GPTs illustrates a different picture. Interestingly we find that the geographical distribution of innovative efforts in GPT fields when these technologies are serving as the secondary technologies moves consistently with that of the foreign share of all technology generation. In other words, in those countries, in which firms significant move their technology activities abroad, they tend to increase the development in GPT fields to support such oversea activities. Moreover, we also find that the internationalization is getting more popular in some emerging economies, such as in South Korea and Taiwan. We also found that the creation of technologies in GPT fields have shifted from some traditional industrial countries such as U.S, U.K and Germany, to some emerging countries, such as some small European countries and other East Asian countries (South Korea and Taiwan), which have been actively exploring new technological opportunities.

Table 17 shows the description of the distribution of patents and Industrial Groups across various nations. We found that U.S account for about half of all patent innovations in the period, followed by Japan which account for about 21%. However, Japan accounts for only 6% share of all Industry-Country-Host Units. It implies that compared with innovations from firms in other countries, the innovations of firm from Japan have been highly concentrated in very few locations (in the home country). Switzerland, instead, has been highly internationalized in their knowledge creation. The 1.16% of all patents is allocated to firms from Switzerland, but they are distributed in 162

Industry-Country-Host units (7.91%).

[Insert Table 17 about here]

5.4.2 Variables

GPTs and the firm's primary technology field (s)

In this study, we applied a same classification measurement of GPT fields as that in study I. The nine GPT fields are Tech5-chemical process, Tech9-synthetic resins and fibers, Tech11-other organic compounds, Tech16-chemical and allied equipment, Tech29-other general industrial equipment, Tech38-electrical devices and systems, Tech39-other general electrical equipment, Tech41-office equipment and Tech53-other instruments and controls.

We also adopted the definition of the primary technology fields as we used in study I. We assume that firms in the same industrial group share the same primary technological field (s). Again, GPT fields and the core technology fields in this study are two separate and independent dimensions in classifying technologies. Any technologies which belong to GPT fields could be core or non-core technologies to a firm. We thus differentiated the general development of technologies in GPT fields (GPT_SHARE) and more particularly the development of technologies GPT fields which lie outside the firm's core fields (NC_GPT_SHARE). The former is measured as the share of all GPT-related patents developed in a firm or in a subunit as opposed to that in non-GPT fields, and the latter is proxied as the share of GPT-related patents which lie in non-core fields as opposed to other non-core technologies.

Dependent Variables

Internationalization of Technology Creation

The degree of internationalization of technological development has been proxied by two variables - the *Foreign Share (FS)* of all activity for the firms of a given industry and the Foreign Share of efforts in the primary technological fields. The foreign share is given by the share of US patents of the largest industrial MNCs in an industry in a given field which is attributable to research invention in foreign locations. At the level of a specific field of activity within an industry, it is defined as:

$$FS_{ij} = FP_{ij} / P_{ij}$$

where *Pij* still denotes the number of US patents granted in a field (j) in a particular industry (i), whilst *FPij* indicates only the number of US patents granted for research conducted outside the home country of the parent firm in the field and industry in question. Similarly, the foreign share of the primary fields (*PFS*) is the foreign share of US patents of the largest MNCs in specific technology field and industry which belong to the primary technological field (s) of each industry. Similarly, to measure the dispersion of the primary technology, we will look at the share of a firm's primary technology which is generated outside the country of origin.

Technological Diversification of Country-Industry Groups

An Industry-Country group is a group of firms that are from the same home country and industry, whereas an Industry-Country-Host group is the industry-country group from a specific host country. Firm-specific characteristics might be sacrificed by taking a generalized study. However, in this particular study we are only interested in the inter-group variations rather than intra-group inter-firm heterogeneities. The sample data include 156 industry-country groups and 1775 subunits (Table 11b).

The proxy for the technological diversification of Industry-Country-Host is based on the consideration that technological diversification is inversely related to the extent of the concentration of the firm's technological specialization. We adopted a similar measurement as to the Entropy measure in Zander (1999)'s study for the degree of technological diversification. It is measured by and the inverse of the coefficient of variation (*CV*) of the shares of patents across all the relevant sectors for the industry-country group. Therefore, in each period considered, the proxies for the SUB TECH DIVE are the reciprocals of the *CV*s, in particular:

$$1/CV_{tech\_MNC} = 1/(\sigma_{tech\_MNC} / \mu_{tech\_MNC}) = \mu_{P_{kj}/\sum_j P_{kj}} / \sigma_{P_{kj}/\sum_j P_{kj}}$$
$$1/CV_{tech\_sub} = 1/(\sigma_{tech\_sub} / \mu_{tech\_sub}) = \mu_{P_{sj}/\sum_j P_{sj}} / \sigma_{P_{sj}/\sum_j P_{sj}}$$

Where *Pkj* denotes the number of patents granted in MNC group *k* and technological field *j*. *Psj* denotes the number of patents granted in subunit *s* and technological field *j*. Moreover, we use the shares of patents in the core technology fields in each MNC group as an alternative dependent variable to test the robustness.

Geographic Dispersion of Innovative Activities of Industry-Country Groups

The location of a patent's invention is recorded in accordance with the origin (country) of the first inventor(s). Similarly, the innovative activity geographical dispersion of the industry-country group (GEO DIS) is measured by the inverse of the coefficient of variation (*CV)* of the share of patents across all subunits within MNC groups, More specifically, the degree of geographic dispersion will be measured by the inversed *CV* (The concentration of variances) of the geographical distribution of all patents generated in each group of firms, which is defined as the share of corporate patents that are attributed to research located in all host countries in each MNC group in each period considered.

$$1/CV_{sub\_MNC} = 1/(\sigma_{sub\_MNC} / \mu_{sub\_MNC}) = \mu_{P_{ks}/\sum_s P_{ks}} / \sigma_{P_{ks}/\sum_s P_{ks}}$$

Where *Pis* denotes the number of patents granted in industry-country group *k* and subunit *s*. Moreover, an alternative dependent variable to measure the degree of geographical dispersion in the robustness test is the number of host countries that a MNC's subunits are sited.

The Share of Core Technologies in Each Industry-Country-Host Unit

The share of the core technologies created in each MNC subunit is measured by the share of the patents which lie in a MNC group's core technological fields, and are invented in specific subunit.

Control Variables

The size of the industry, the patent stocks of the industry-country groups and industry in terms of share of patents in each MNC group as compared to that of all MNC groups in the industry, and share of patents in each industry as compared to that in all industries, the degree of international exposure of the MNC group in terms of the number of subunits and the size of the technological field might affect the degree of technological diversification, geographical expansion and the share of innovative activities abroad, so we control for these factors in the regressions.

5.5. Empirical Findings and conclusions

5.5.1 Statistical descriptions

We found that the shares of core technology (ies) in each industry-country group have been declining over three periods considered (Graph 1). This implies that firms have tended on average to become more technologically diversified over time. By contrast, among the innovations in a firm's core fields, an increasing proportion of these core technology creations have been taken by the firm's foreign affiliates. This seems contradictory to existing literature on which has emphasized the home-based R&Ds of corporate core competencies (Cantwell and Janne, 1999). However, this trend also implies that MNCs have been re-structuring their international innovation networks to better exploit locational advantages embedded in the host countries.

We also find in Graph 1, 2 and 3 that while the degree of technological diversifications of Industry-Country group stay fairly stable over three periods, a few foreign subunits (Industry-Country-Host) within MNC groups in most recent period (1987-1995) have become much more technologically diversified. This finding is consistent with recent discussions in IB literature that in ever more closely integrated international networks (Hedlund, 1986; Bartlett and Ghoshal, 1989), foreign technological activities carried out by foreign affiliates are not limited to exploiting existing competencies, but rather targeting at new ones. These foreign subsidiaries which have shifted away from a firm's existing technology core areas are considered as new centers of excellence.

[Insert Graph 1, Graph 2 and Graph 3 about here]

5.5.2 Regression results and conclusions

The Pattern of Internationalization of GPTs and Other Technologies

We took two levels of analysis in this study. The first set of analysis is to look at the internationalization of technology creations in specific sectors, while the second is to associate the internationalization of technological development in GPT fields to a MNC's strategy in allocating its R&D efforts. The patent and Industry-Country Group analyses are designed to find some empirical evidences to illustrate the geographical change of innovations in GPT fields.

The Pair-Wise correlation coefficients of the variables are listed in Table 18. We found in the table that there is no major multicollinarility problem in our models. Assuming that variables - the shares of 56 technology fields in the industrial groups of firms, the shares of industrial groups which are using certain technologies, the share of the primary technologies, and the share of technologies innovated in host countries by each industrial group of firms - are all normally distributed, to examine the linkage between the change of technology structure and the geographical re-allocation of innovative activities, we adopt the OLS regressions in the first part. Moreover, we take GLS (fixed-effect and random effect) regressions to find out the relationship between the extent of GPT development and firm structure change, to control for the Industry-Country and Industry-Country-Host heterogeneities.

[Insert Table 18 about here]

The regression results on the first set of analysis are summarized in Table 19 and Table 20. Model 1 through 5 (Table 19) are designed to examine the degree of internationalization of MNC innovative activities by looking at whether these activities were taken in home or foreign countries. In model 6 to model 8 (Table X), we further disaggregate the home or foreign country of each patent in accordance with its country of origin. Our sample data cover the patents created by subunits located in 62 host countries which belong to MNC groups from 46 home countries.

[Insert Table 19 about here]

In Model 1, we found that across all industries, GPTs negatively link with the foreign share of MNC innovative activities. This is consistent with the proposition that given the tacit nature, compared with the non-GPT technologies, technologies in the GPT fields are more likely to be created in the home countries. Similarly, the result in model 2 shows that the innovation activities on GPTs are mainly home-based, and this finding is especially true when these technologies lay in the primary areas in a firm's technological profile. Model 4 provides more salient evidence to this proposition. More specifically, the negative coefficients (-.034) on the GPT-based industry, the ICT-based industry (-.029, the industries based on the advanced type of GPTs) and on the firm's primary technology fields (-.033) suggest that firms in the industries in which GPTs serve as primary technologies are less likely to create their primary technologies in foreign facilities. These results also help support the second part of our hypotheses, that within the international innovation network of each industrial group of MNCs, compared with other technologies, the creation of GPTs which are outside a firm's primary technology fields tends to have higher degree of internationalization.

This study is not limited to investigate the geographical distribution of innovative activities in the GPT fields. We also intend to explore the role of these technologies in the evolution of the MNC international innovation network. We took more tests to examine the impact of GPTs-related innovative activities on the internationalization of the MNC's overall innovation networks. Results in model 6 supports our previous proposition that controlled for all other factors, in more recent years the innovations of a firm's primary technologies are increasingly re-allocated outside its home country (with the coefficient 1.092 in the third period). In other words, within each MNC, the foreign affiliates located in an increasing number of countries are involved into the development of the firm's core technological areas. As we have discussed, to some extent the change in the share of a firm's primary technology fields implies the technological diversification of the firm in study, this result from another perspective shows that there tend to be a co-evolution of the technological diversification along with the internationalization of the MNC's innovations. This conclusion is consistent with the discussions in IB literature (Cantwell and Piscitello, 2000; Pearce, 1989), while further helps explain one important driving force behind this sectoral-geographical dynamism.

The empirical result in Model 7 helps us conclude that control for other factors, there tends to be a higher degree of internationalization of the MNC's innovations, as the MNCs enhance the development of the secondary technologies (non-primary) in GPT fields (the coefficient is 0.67). This is also true when firms are focused on developing more supporting technologies (non-primary) in the ICT fields. Although we got a positive coefficient (0.35) in the non-primary ICT fields, this result is not significant.

Model 5 is focused on the relationship between technological restructuring and geographical re-allocation of innovative activities. The result shows that controlling the overall technology share created in foreign countries, the distribution of GPTs in case that they serve as a firm's primary technologies tend to be less dispersed. This is also consistent with our findings in previous models. More important, we expect that the creation of GPTs across all MNCs tend to rely on an ever more dispersed network, give that an increasing proportion of these technologies are created to support a firm's primary technological areas. This finding is also strongly supported by the result in model 9. It is shown that controlling for the share of primary technology field in each industrial group, the innovation activities in GPTs-based firms (-.049) and in ICT-based firms (-.045) will be less internationalized.

Overall, most of the hypotheses are supported. Our study suggests that the development of GPTs have a high speed growth in the new techno-economic paradigm. These technologies, when serving as a firm's primary technological areas are still likely to be remained in the home countries. In general, the degree of geographical dispersion of this re-allocation tends to increase over time. While the firm's primary technologies are still created at home. There is a trend that increasingly more technologies in the firm's core areas are moved to the centers of excellence abroad (Cantwell and Janne, 1999; Kuemmerle, 1997; Zander, 1998), to take advantages of local technological specialization.

[Insert Table 20 about here]

The restructuring of the International Innovation Networks of MNCs

The correlation matrix of variables of the second set of analyses is listed in Table 21. It shows that there are no major multicollinarility problems associated with the variables. Given that all dependent variables – TECH DIV, GEO DIS, SUB TECH DIV and SUB PSHARE are normally distributed, to control the firm and subunit heterogeneities, we use fixed-effect and random-effect GLS regressions in testing the relationship between the development of GPTs and the change on the technological and geographical patterns of corporate innovative activities. Moreover, Hausman test is taken for testing robustness for fixed and random effect regressions.

[Insert Table 21 about here]

The hypotheses are tested in two set of regressions. Models 1 through 5 are designed to examine the influence of GPT and NON-CORE GPT development upon MNC technological and geographical diversifications (TECH DIV and GEO DIS). Model 6 to model 13 further tests whether the development of GPTs and NON-CORE GPTs is related to the change in the pattern of MNC international innovative activities, and whether the co-evolution of MNC TECH DIV and GEO DIS is accompanied with a shift of innovative activities in the core fields of a MNC away from headquarters to selected foreign subsidiaries. The fixed-effect GLS regression results for the two sets of analyses are summarized in Table 22 and Table 23.

[Insert Table 22 and 23 about here]

Model 2 and Model 3 are designed for testing Hypothesis 1. Model 2 and Model 3 show that although the development of GPTs in general (GPT_S) appears to be negatively associated with the TECH DIV (degree of technological diversification) of a MNC group, when these GPTs are outside the core fields, they are positively associated with technological diversification of the MNC group. Hypothesis 1 is strongly supported. GPTs, as the supporting technologies are employed as a “bridge” that brings together a firm’s core technologies and other technologically less related knowledge. Consequently, the efforts in these fields facilitate technological diversification.

Model 4 and 5 help us understand the change of the geographical distribution of MNC innovative activities. There is no strong evidence showing that the development of technologies in GPT fields which represent the secondary fields of a MNC group tended to rely on an ever more geographically dispersed innovation network. When we further took a partial correlation test between TECH DIV and GEO DIS controlling for the development of GPTs as non-core technologies, the relationship between GEO DIS and TECH DIV becomes significantly positive. These results are consistent with knowledge-based view in MNC growth that across all MNC groups, the affiliates located in an increasing number of countries contribute to the development of technologies. Moreover, this trend is likely to be associated with the geographical dispersion of innovative activities in GPT fields.

We further deepen our understanding of how does the development in GPT fields and in particular GPTs as the non-core technologies help change the pattern of MNC international innovation networks. Models 6 through 13 are tested at subunit level, focused on the relationship between the specialization on GPTs and geographical re-allocations of certain innovative activities within firms (Hypothesis 3 and 4). In hypothesis 3 we proposed that the shift of a firm's technological activities in principle fields towards foreign R&D facilities is accompanied with the local development of GPTs in such subsidiaries. More specifically, results in model 6 and model 7 reveal that both GPTs and non-core GPTs are positively associated with the share of core technologies developed in subunits. This is conclusion is consistent with our discussion that the critical role of GPTs in corporate innovations is to fuse a firm's existing knowledge in core areas with new inputs from different domains. Since headquarters of MNC groups are also considered subunits in this study. Parent firms of MNCs historically take more R&D activities in the core fields than foreign subsidiaries. At this point, the positive relationship shown in model 7 might be biased. This is also true when we added a "foreign" dummy in model 8 and then removed all "parent firm" observations in model 9. Taking all other factors controlled, the share of GPTs in the non-core areas in a subunit is strongly and positively associated with SUB PSHARE. As we expected, as increasingly more innovative activities in primary areas are off-shored to the firm's foreign subsidiaries, these subsidiaries need to develop GPTs locally to help integrate and combine them into their technological portfolio.

Finally, hypothesis 4 is strongly supported by model 10, 11, 12 and 13. In model 10, taking all other factors controlled, in spite of a strong negative relationship between local development of GPTs as a whole and the share of the innovative activities in primary fields in subunits, we do find a positive relationship between the extent of GPT development when these technologies are generated as supporting technologies and technological diversification at subunit level. Given the same argument that theoretically, parent firms of MNC groups tend to be more proliferating in R&D outputs and technologically diversified than foreign subunits, and that the relationships shown in model 10 and 11 might be biased because the degrees of diversification (SUB TECH DIV) at subunit level are overstated. We test hypothesis 4 in model 12 and 13 by adding a "foreign" dummy variable and only keeping the foreign subunit observations. Again, we find that both "the share of non-core GPTs" and "foreign" show positive coefficients, and they are statistically significant. This result strongly supports our hypothesis 4. More specifically, GPTs that are created as the supporting technologies in subunits tend to facilitate the technological diversification in such facilities.

Robustness Tests

Model 14 to model 17 are designed for testing the robustness. In the first test (Model 14), we substituted the degree of internationalization of innovation activities across all technology fields (TECH INTL) which is measured by 1/CV of the share of innovation activities in each field across all host countries, with the share of innovations in a specific technology field that is generated in foreign countries. The result is consistent with what we got in model 1. It shows that compared with GPTs as any fields, GPTs in the secondary fields are more likely to be generated in foreign countries. Moreover, the core technologies are more likely to be remained at home country.

Moreover, given that large firms are getting more technologically diversified nowadays, most of them are likely to take innovation activities across many technology fields. At this point, to proxy the degree of corporate technological diversification based on the Concentration of Variances measurement might be biased. Thus, we replace the firm TECH DIV with the share of patenting activities in a firm's primary technology fields. A decrease in patenting activities in a firm's core areas implies an increase in the firm's R&D efforts in other fields. The result in model 15 helps us draw the same conclusion that although patenting activities in a firm's GPT fields are positively related to those in the primary fields. When these GPT-related activities lie outside a firm's primary fields, however, they are negatively associated with a firm's efforts in the core areas. In other words, the non-core GPTs are facilitating corporate technological diversification. In the third test (model 17), we replace the GEO DIS of a specific MNC group with the number of host countries in which the MNC group is taking innovative activities, and we draw same conclusions with the result in this test.

Lastly, model 16 and model 18 are testing whether the GPTs in the core technology fields are associated with the technological and geographical diversification of MNC groups by using the GPT_BASED_MNC, which is the MNC group from the industry in which GPTs lie in the primary fields. The result shows that there tends to be a higher degree of technological diversification for GPT-based MNC groups, but these firms tend to be less geographically expanded. This finding is consistent with the previous finding that GPTs in general are not associated with corporate geographical dispersion.

[Insert Table 24 about here]

Chapter 6. Knowledge Accumulation, Intra-firm Innovation Networks and Centers of excellence in MNCs

6.1. Introduction

GPTs are a “driving force” in economic growth, especially in technological progress over eras (Granstrand, Patel and Pavitt, 1997). Since they are widely applicable to various research activities, they play a “bridging” role in the fusion between sectorally separate technologies. This is especially true in recent time in which a new Techno-Economic paradigm has emerged.

In this context, multinational corporations (MNCs) are seeking for a more efficient way to build new competencies by exploring synergies of their existing technologies with new ones. The new paradigm is interplaying with a further reduction of spatial barriers and the dynamic economies of scope (Teece, 1997). The latter is reflected as the interaction between geographically dispersed R&D facilities and the ever diversified technology profile of innovative activities of MNCs. To illustrate, Boeing has established R&D centers worldwide including those in Seattle (WA, Headquarter), Chicago (IL), Japan, Australia, Saudi Arabia and Brazil, etc. These centers are carrying out innovations in a wide range of technology sectors (mechanical engineering, chemical process, materials, communication, powers, etc.). These subsidiaries not only exploit Boeing’s existing competencies in airplane manufacturing, but are helping the firm to explore new growth alternatives.

At least some foreign subsidiaries embody a set of capabilities that has been explicitly recognized by the firm as an important source of value creation (Frost, et al., 2002), rather than simply replicating technology competencies, and thus play a strategic role within the MNC group. They become what we called the “competence-creating” subsidiaries (Cantwell and Mudambi, 2005; Kuemmerle, 1999), through which the MNC’s “global synthesis” process - the integration of knowledge flows from diverse sources (Buckley and Carter, 1996) - could be undertaken in the host locations (Birkinshaw and Hood, 1998). MNCs therefore are able to create firm-specific advantages by transferring knowledge across these geographically dispersed facilities (Gupta and Govindrajan, 2000; Hansen and Lovas, 2004; Almeida, 1996).

Building upon existing arguments about corporate technological diversification, internationalization and their co-evolution, and our conclusions from previous chapters, this study is aimed to explain the determinant of knowledge accumulation and acquisition of foreign subsidiaries in host regions. We found that the specialization on GPTs enables localized knowledge to be accessed or transferred more readily between geographically distant and sectorally diversified facilities. Therefore, local development and application of GPTs facilitates a more favorable interaction between the foreign subsidiaries of MNCs and other firms in the host locations where the subsidiaries are located. In a dynamic view, this allows firms from a wider range of industries to cluster in the host regions and thus increases the diversification of regional innovation systems. The empirical model is shown in Figure 5.

[Insert Figure 5 about here]

Another important contribution of this study is to re-classify the GPT fields by tracking patent citations. The cross-field approach has been adopted in Hall and Trajtenberg (2004)'s study. As compared with the cross-industry classification, which is focused on the creation of technologies, the cross-field classification emphasizes the "application" aspect. The comparison and contrast of the two methods provide a research platform for future research in GPTs.

Moreover, by bringing in the concept of GPTs in cluster literature, this study addresses a gap in the conventional IB and Strategy research, of which R&D co-location has long been examined from a static approach (distinction between specialized and all-around centers (Marshall, 1890, Arrow, 1962, and Romer, 1986, Jacobs, 1969). This study, instead, is aimed at the evolution of innovation clusters by examining the underlying technological trajectory dynamism.

The rest of this paper will be organized in five parts. In the following section, we review literature in GPTs, the evolution of MNC international innovation networks and the regional innovation system. Then we will discuss the natures of GPTs, linking them to broad innovation networks, following by the hypotheses. The fourth section is focused on data, the construct of variables and research design. The fifth section is devoted to some empirical results, discussions and conclusions. Some implementations and the directions of future research will also be covered in the last part.

6.2. Literature Review

6.2.1 The Centers of Excellence of MNCs

In early studies, advanced R&D capabilities of MNCs are believed to be located in the home countries (Behrman and Fischer, 1979; Cheng and Bolon, 1993; Granstrand et al, 1993). More recently, the concepts of 'centers of excellence' and 'competence-creating subsidiary' (Bartlett and Ghoshal, 1986) remedy the subsidiary focus of earlier views. Foreign subsidiaries followed an evolutionary path from performing technology replication to support local market to becoming global innovative centers (Ronstadt, 1977). Increasingly more subsidiaries have gained a creative role, generating new technologies in accordance with the competitive advantages of the country and region in which they are located (Cantwell, 1989, 1995; Pearce, 1997; 1999; Zander, 1999; Almeida, 1996). This type of subsidiaries embodies a set of capabilities that has been explicitly recognized by the firm as an important source of value creation (Frost, et al., 2002).

Foreign subsidiaries significantly acquire local technologies to 1) offset home country weakness (Almeida, 1996); 2) monitor and assimilate foreign technology Hakanson and Nobel (1993); and 3) supply technology which is complementary to the primary technological capabilities available in the home market (Cantwell and Randaccio, 1992). Phene and Almeida (2003) found some positive changes in the scale and scope of innovative activity across subsidiaries which suggest a subsidiary-level technological diversification.

In explaining the geographical source of technology creations of multinational firms, while geographical economists have emphasized the "stickiness" nature of technological activities in national or regional innovation systems, given that newly-created knowledge can be appropriated only to a limited extent, contributions in IB literature have been increasingly interested in the advantages of international knowledge transfer and a shift away from systems of independent locally oriented affiliates towards a globally or regionally integrated network (Hedlund, 1986; Porter, 1986; Bartlett and Ghoshal, 1989). The international integrated networks allow multinational firms to locate their R&D efforts in optimal places where they could take “locational” advantages where the foreign subsidiaries are sited.

At this point, how MNCs integrate the knowledge sourced from host locations and transfer it among subunits in technologically diversified locations (Gupta and Govindrajan, 2000; Hansen and Lovas, 2004) is worthy investigating. Since the mid 1980s, a growing stream of research shows interests on the headquarters-subsidiary relationships. However, in these studies, attentions have been primarily paid to the managerial mechanism that MNCs use to coordinate their network of subsidiaries (Bartlett and Ghoshal, 1989; Ghoshal and Nohria, 1989; Cantwell and Mudambi, 2005), or on the interdependence nature of subsidiaries, or the distinction exploitation and exploration types of activities of foreign subsidiaries (Ghoshal and Bartlett, 1988; Gupta and Govindarajan, 1991;), while how are the “synthesis” and the “coherence” associated with the firm’s underlying technology trajectory has been remained unanswered.

6.2.2 Regional Innovation Centers

As we have discussed, numerous studies have demonstrated that nations and regions differ in their ability to attract international R&D (Cantwell, 1989; Patel and Pavitt, 1995; Porter and Solvell, 1998), and emerge as “centers of excellence” for the MNC groups given some particular advantages of innovation (Cantwell, 1995; Nelson, 1993). In host regions of MNCs, spatial proximity mechanisms strongly influence the knowledge sourcing activities of MNC through their foreign subsidiaries. However, due to the “tacit” nature of industrial technologies (Nelson and Winter, 1982), there are significant barriers to the diffusion of knowledge across sectoral distinct entities, even within the geographical boundaries.

Two types of regional innovation centers have been discussed in literature. The specialized centers (Marshall, 1890, Arrow, 1962, and Romer, 1986) are highly specialized in their profile of technological development, and attracting corporate activities in the same narrow range of fields. A typical case for this type of locally specialized cluster is Silicon Valley. However, Jacobs (1969) argues that knowledge may spillover between complimentary rather than similar industries, and it is the exchange of complimentary knowledge that facilitates search and experimentation in innovation. This is what we called the All-around centers in which the development efforts of firms from a broad range of sectors agglomerate. New York City in the United States, Shanghai in China and London in U.K are typical examples of the latter case.

The Jacobian clustering theory has been linked with urbanization theory, and mainly focused on the foundation of local infrastructures such as transportation, communication, and education. The exchange of complimentary knowledge that facilitates search and experimentation in innovation, however, has been less studied (Harrison et al., 1996). Our study is aimed at explaining the inter-industry knowledge diffusion associated with the existence of firms working in several different fields of research but with a common overlapping interest connected by certain general purpose technologies, which are relevant in most industries. This argument further leads to an evolutionary theory on cluster change.

6.3. Theoretical Development and Hypotheses

6.3.1 Knowledge Accumulation and acquisition of Foreign Subsidiaries in Host

Countries

Firms under the pressure of the ever more complex combinations required within the cutting-edge technologies and the uncertainty associated with high R&D costs, need to cumulate expertise in multiple technological fields (Granstrand et al., 1997; Patel and Pavitt, 1997). Organizational and geographical boundaries may not fully encompass entirely the generation of new technologies. The capabilities sourced from host countries and regions to a large extent complement a firm's primary technologies which have been restricted at home. Moreover, multinational firms explore new growth alternatives and build new competencies in foreign countries based upon existing ones. In the new technology paradigm, the internationalization of advanced technological capabilities became more associated with new growth opportunities and flexibility advantages.

The new opportunities mainly come from explorative activities. Organizational learning literature makes a distinction between (March, 1991) exploration activities and exploitation activities. In exploration activities the scope of innovative search may be broadened, and is more likely to incorporate resources that lie outside of the organization's existing network. Based on this construct, subsidiaries of multinational firms may be broadly classified as those with an exploitation mandate and those with an exploration mandate (Cantwell and Mudambi, 2005; Kuemmerle, 1999). In latter case, subsidiaries are directed toward the development of new technical capabilities and knowledge. Exploring activities are very likely to occur in foreign countries. This is because the technology profile of each location is historically bounded and distinct over time (Dosi, Teece and Winter, 1992). Here not only the market signals from important local customers, but also the needs to extract distinctive technical skills and resources complementary to the rest part of the corporate groups are likely to drive the pattern of innovative search (Vernon, 1979; Kogut, 1989, 1990).

This shift of innovation efforts is more likely to take place in those subunits which have gained experience and accumulated knowledge in certain fields (Zander and Solvell, 2000; Birkinshaw, 1997). Subsidiaries generating more technologies which could be used in a broad range of areas such as GPTs tend to have more opportunities to bring together inter-related and complex technologies. The very "connective" nature of GPTs enables the "combination" and "fusion" with knowledge in other fields, firms and industries. GPTs work as "bridge" linking the existing technologies to other non-GPT capabilities sourced from host locations. This process may follow a continued virtuous circle, that knowledge sourcing creates new opportunities for MNCs to reinforce, shift and expand their existing cores fast. Therefore, we expect a higher degree of technological diversification for individual subsidiaries when they have largely developed GPTs as supporting technologies, and these subsidiaries tend to have larger shares of innovative activities compared with other subunits within the MNC group.

Hypothesis 1: Compared with other technologies, GPTs are more likely to be applied to support other technologies.

Hypothesis 2a: Compared with other technologies, GPTs are more likely to be applied to support the innovations in a firm's core technology field (cited by).

Hypothesis 2b: Compared with other technologies, GPTs are more likely to be applied to support the innovations in a subsidiary's core technology field (cited by).

Hypothesis 3: Compared with other technologies, GPTs are more likely to assist a firm's foreign subsidiary create competencies in distant fields.

Hypothesis 4a: *There is a positive relationship between innovative activities in GPT fields in a foreign subsidiary when they lie outside a firm's primary fields and the degree of technological diversification of that subsidiary.*

Hypothesis 4b: *There is a positive relationship between innovative activities in GPT fields in a foreign subsidiary when they lie outside a firm's primary fields and the extent of innovations of that subsidiary.*

Here GPTs and the primary technology fields are two separate and independent dimensions to classify technologies. Any technologies which belong to GPT fields could be the primary or non primary technologies to a firm. To illustrate, computing technologies are GPTs and are the primary technologies for IT firms such as Microsoft and Google, but they are supporting technologies for firms in other industries as the Boeing Co. and Roche.

The location advantages are transferred to other subsidiaries to create a "cross-complementary" advantage within the MNC group through the established intra-organizational mechanisms (Cohen and Levinthal, 1989). Internationalization in terms of international exchange of knowledge creates new opportunities for generating innovative profits through a more intensive interaction in the corporate learning process (Cantwell and Santangelo, 2000). More specifically, the specialization in GPT fields allows a higher degree of locational dispersion of the innovative activities of MNC groups. Over time, there tends to be virtuous circle in technological evolution in each MNC group. This intra-firm network, through an internally coordinated learning and leveraging process, will complements the external inter-firm networks.

Hypothesis 5: *There is a positive relationship between innovative activities in GPT* *fields lying outside a firm's primary fields and the dispersion of innovative activities of that firm in different locations the host country.*

6.3.2 The Role of GPTs in Evolution of Regional Innovation Centers

The extent of influences of subsidiary technological innovation partially depends on the characteristics of the knowledge network and the knowledge linkages of the subsidiary with other entities (Almeida and Phene, 2004; Birkinshaw and Hood, 1997). This argument is especially true for innovation activities in certain innovation clusters in which subsidiaries are sited.

The new economic geography (Arthur, 1990; Grossman and Helpman, 1991; Krugman, 1991; Romer, 1990) suggests that economic activities and technology development are spatially concentrated, because of the restricted mobility of knowledge embedded in social capital (Malmberg, et, al., 1996; 1998), and spatially bounded increasing returns. This concentration is crucial for the generation and diffusion of knowledge among agents (Freeman, 1991; Storper, 1992) within the regional innovation network. By benefiting from each others' research' (Griliches, 1979), the spillovers may increase the stock of knowledge available for each individual firm. However, given that newly-created knowledge can be appropriated only to a limited extent, and the technological change is cumulative and path-dependent, knowledge spillovers are believed to occur only to firms which taking similar technological activities. Consequently, the innovative activities of regional clusters tend to maintain their position over time.

From an evolutionary perspective, technological broadness of an innovation center is not static, but changes over time. Technological interrelatedness between firms is the foundation of inter-firm knowledge spillover and technological exchange (Combes, 2000). Like that of firms, technological base of innovative centers also need to be broadened. This is not only because the firms sited in each location themselves are becoming more technological diversified, but because firms in order to extend their lines of domestic specialization (core technologies), need to draw on some general capabilities in host locations.

In the latter case, knowledge creation is the product of localized search and knowledge sharing (Cyert and March, 1963, Nelson and Winter, 1982), which depends upon the technology relatedness between innovative activities in various domains. GPTs, given their unique nature of being generally created in the firms of a broad range of industries, are viewed as lying in the heart of cross-industry innovation. They help overcome the barriers to the diffusion of knowledge across industrial environments or systems of innovation (Malmberg, et, al., 1996; Solvell and Zander, 1998), and connect technologies between separate sectors. By doing this, GPTs as supporting technologies facilitate a favorable interaction between innovation activities in different technologies fields as well as the knowledge flows among firms, universities and other public research institutions. The specialization of GPTs when they are developed as supporting technologies will allow a higher degree of technological and industrial dispersion within innovative centers by facilitating knowledge fusion and technology transfers of innovations across many industries and in various sectors. Meanwhile, given that the local technological diversity across industries may promote innovation and knowledge spillovers (Cantwell and Piscitello, 2000). These activities will in turn reinforce locational advantages of the host country and region (Cantwell, 1992; Florida and

Kenney, 1994; Krugman, 1990; Porter, 1990).

Hypothesis 6: *The extent of innovative activities in GPT fields in an innovative center is positively associated with industrial diversification of that regional innovation center.*

6.4. Data and Methodology

6.4.1 Data

The research setting of this study is corporate innovative activities proxied by patents created by the world's large industrial firms from non-US countries and their subsidiaries in the U.S from 1969 to 1995, as well as the citations of these patents back to 1890. The dataset concludes totally 77,851 patents that have been innovated by the U.S affiliates of largest foreign firms in the USPTO system (the United State Patents and Trademark Office) from 1969 to 1995. We also track totally 135,084 patents that have been cited by the formers. All patents and patent citations are from a database that have been created and updated in Rutgers University.

The citing patents are organized as a panel of patents indexed by the year of being granted, the MNC group to which the patents belong, the technology field that the patenting activities are classified in USPTO system, the country of origin of each MNC, and the U.S state that the patents have been invented. The country of origin and the U.S state of each patent are identified by the location of the first inventor(s) in that patent. The data thus include patents of over 300 MNCs that are originated from about 20 countries in the world. For citation data, we only record the technology classification and granted year for each cited patent in study.

Again, the citing patents are consolidated by corporate groups where they were assigned to affiliates a parent company under common ownership. Births, deaths, M&A as well as the occasional movement of firms between industries have been taken into concern in this study. Each corporate group is in turn allocated to an industry on the basis of its main products, these being one of 16 industrial groups. Moreover, each patent is allocated to one of 399 US patent classes according to the type of technological activity with which each patent is most associated, which in turn belong to one of 56 technological fields. The technological field classification of patents and the industry of the firms to which patents were assigned are recorded separately.

We take three levels of analysis in this study, we first focus on the patent citations, revisiting the general natures of GPTs that we have explored in study I. We then move to subsidiary level to look at the innovation activities occurring in the U.S taken by the foreign subsidiaries in the U.S in the period of study. In the latter analysis, the sample data is constituted by an unbalanced panel data covering 35, 662 citing patents which have been created in at least one of the 54 states (areas) in the U.S in the period of study. The patents belong to 306 firms which are originally from 20 foreign countries. We lastly investigate how GPTs help foreign subsidiaries accumulate knowledge in different geographical locations.

6.4.2 Variables

Independent Variables

As we have mentioned in earlier section, a major contribution of this study is to complement the exiting industry-based measurement of GPTs that we have created in Chapter 3 and Chapter 4, by using the citation-based cross field approach. Unlike in study I and study II, in which we define GPTs as being “generally created” by firms across many industries, here we define GPT fields as technology fields in which innovations have been widely applied. In other words technologies in GPT fields have a wider technology base compared with technologies in other sectors. More specifically, we classified GPT fields in a cross-industry innovation application approach as we discussed in Chapter 3.

Primary Technology Field (s)

We use the same definition of the primary technology fields as we adopted in study I and study II. We classify the primary fields of each industry by comparing the relative concentrations of technologies created in each industry, with the relative sizes of industries taken into concerns. As we discussed earlier, our analysis is based on the assumption that firms from the same industry group share same primary technologies, and thus a MNC's core technology fields are the primary technology fields of the industry.

Again, the GPT fields and primary technology fields are two distinct constructs in classifying technologies. The specialization in GPT fields of a subunit is measured by the share of patents which belong to GPT fields in each subunit of MNCs in the U.S. Therefore, GPTs as a firm's supporting technologies are distinct from GPTs that are created as primary technologies in a firm and also distinct from other technologies that are created as peripheral technologies.

Moreover, his study is focused on the innovative activities of foreign subsidiaries in the U.S. The motivations and focus of innovations, and knowledge acquisition in foreign markets might differ from that in home countries. Therefore we differentiate the core technology fields of the affiliates of a MNC in the U.S from those of the MNC (industry).

We assume that firms in the same industrial group tend to share the same primary technological field (s). We define the subsidiary core fields by calculating the RTA index of subunits of each MNC in the U.S to define the core fields in the subunit level. The RTA of subunit *k* is defined as:

$$RTA_{kj} = (P_{kj} / \sum_k P_{kj}) / (\sum_j P_{kj} / \sum_{kj} P_{kj})$$

where Pkj denotes the share of patents in technology field j invented by subunit k.

In this study, both citing and cited patents are classified as GPTs or non-GPTs, and we distinguish whether the citing and cited patents are primary or peripheral for a subunit or a MNC. Moreover, we link the share of technology creations in GPTs fields in each subunit to the innovative activities in that subunit. The extent of development of technologies in GPT fields as supporting technologies in a subunit is measured by the share of the patents which are in GPT fields but lie outside a firm’s primary technological fields in that subunit.

Dependent Variables

Citation Analysis

Co-citations and intra-field citations

Co-citation (CO-CI) in this study is refered to the cited patent that has been co-cited with other cited patent. CO-CI is 0 if there is only one cited patent for a specific citing patent. Intra-field citation (ITECH-CI) is defined as the case that the cited patent is in the same technology field as that of the citing patent. We also create two dependent variables Sub Core (S-CORE) and MNC Core (F-CORE) to measure the citation activities associated with the core technology creation of MNC groups (industry) and the subunits in the U.S of that MNC group. The citation level analysis is to further explain the natures of GPTs and to examine the inter-dependence between GPTs and other technology fields, especially the core fields of a given MNC group or subsidiaries in building corporate technological competencies.

Regions

The classification of regional innovation centers of this study is derived from the geographic information contained in each patent. The classification of regional divisions is based on the designation of nine Census Bureau divisions (CBD) created by U.S Census Bureau. The nine divisions are:

Area 1 (Northeast)

Division 1 (New England) Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut

Division 2 (Mid-Atlantic) New York, Pennsylvania, New Jersey,

Area 2 (Midwest)

Division 3 (East North Central) Wisconsin, Michigan, Illinois, Indiana, Ohio

Division 4 (West North Central) Missouri, North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa

Area 3 (South)

Division 5 (South Atlantic) Delaware, Maryland, District of Columbia, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida

Division 6 (East South Central) Kentucky, Tennessee, Mississippi, Alabama

Division 7 (West South Central) Oklahoma, Texas, Arkansas, Louisiana

Area 4 (West)

Division 8 (Mountain) Idaho, Montana, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico

Division 9 (Pacific) Alaska, Washington, Oregon, California, Hawaii

Not surprisingly, the technological concentration of each geographical division is consistent with theoretical discussions in literature. For instance, in division 9 which covers Washington and California, we observe a higher concentration of innovative activities in Office Equipment and Professional and scientific instruments industries, while innovative activities in Transportation industry are agglomerated in division 3 (Michigan and Wisconsin). It also shows that division 2 (New York, New Jersey and Pennsylvania) has innovative activities in almost all industries. This area is likely to be the "all-around" technology center in literature.

Table 25 and 26 shows the distribution of citing and cited patents in each CBD according to the technology fields. It is illustrated that innovations in GPT fields are most concentrated in technology clusters like CBD 2 (New York, New Jersey and Pennsylvania, etc.), CBD 3 (Michigan and Illinois area), CBD 7 (Texas area), and CBD 9 (California and Washington). More specifically, we also found that GPTs in the old paradigm such as Chemical Process, Chemical Equipment and General Industrial Equipment are located in the traditional developed area such as CBD 2 and CBD 7 which are based on energy and oil-related technologies, while new ICT-related technologies are mostly to be found in Pacific area (CBD 9).

[Insert Table 25 and 26 about here]

Normally, firms cite other patents that are closely related to their innovations. It is thus interesting to compare the innovation and citation activities of firms located in different regions (Table 27, 28 and 29) to find out the technology structures of these areas.

Firms tend to cite a large amount of patents that are peripheral but related to their core areas. To illustrate, in Table X we found that firms in Pacific Coast area have cited a much higher proportion of cited patents compared with their innovations in certain sectors, such as in Transport Equipment (Tech 47) and Mechanical calculators and typewriters (Tech 30). Meanwhile firms in this area have invented a much higher proportion of technologies than what they have cited in some other fields such as Aircraft Technology (Tech 44) and Woodworking Tools and Machinery (Tech 27). This comparison can be explained by the evolution of industries in this area, where there are large aircraft industries (Boeing Co. and their affiliates) which have heavily innovated aircraft technologies, but need complementary technologies in other fields to support their core technologies, such as Other Transportation Equipments. This is also true for the growth of ICT businesses in this area. ICT firms in Silicon Valley and Washington State need to cite mechanical calculators and typewriters to develop their new information technologies.

[Insert Table 27, 28 and 29 about here]

Firm Analysis

Degree of Technological Diversification of Subunit

The subunit innovation is identified as the patents that have been innovated in the U.S. For instance, Schering Co. (Germany). has innovation activities in New York, Ohio, Texas and Wisconsin and California respectively. Each location is thus identified as a subunit of Schering Co in the U.S.

The degree of technological diversification of a specific foreign subunit is measured by the inverse of the Concentration of Variances (CV) of the shares of patents across 56 technological fields generated by the subunit of MNCs in each year. In other words, we look at the broadness of a subunit's technological base.

$$1/CV_{tech\_sub} = 1/(\sigma_{tech\_sub} / \mu_{tech\_sub}) = \mu_{P_{kj}/\sum_j P_{kj}} / \sigma_{P_{kj}/\sum_j P_{kj}}$$

Where P*kj* denotes the number of patents granted in subunit k and technological field j.

Dispersion of MNC Innovative Activities in Host Countries

To measure the degree of geographical dispersion of innovative activities of MNC sub-units, we adopted a similar measurement as the Entropy measure which Zander (1999) has used. In this study, the degree of geographic dispersion is measured by the inverse of the *CV*[13] of the geographical distribution (across all subunits) of all patents generated in each industrial group of firms.

$$1/CV_{sub\_MNC} = 1/(\sigma_{subshare} / \mu_{subshare}) = \mu_{P_{km}/\sum_m P_{km}} / \sigma_{P_{km}/\sum_m P_{km}}$$

Where P*km* denotes the number of patents granted in subunit *k* and firm *m*.

Region Analysis

Diversification of Regional Innovation Centers

To examine the degree of technological diversification of each innovation center, we look at the Concentration of Variances (C.V) of distribution of all technology fields in each division. The industrial diversification or composition of an innovation center is proxied by the *CV* of technological activities of firms from various industries in that division. Furthermore, both the degree of technological diversification of each foreign subunit and the degree of sectoral dispersion of a given innovation center tend to increase over time.

[13] The concentration of variances

Control variables

Industry-specific, sub-specific and location-specific characteristics are controlled in this study. Moreover, as we have discussed earlier, firms in certain industries and from certain countries account for a large amount of patents and patent citations, and might thus bias our regression results. We control for these factors. In the citation-level analysis, we control the following factors: Chemical industry, firm from UK, Germany and Switzerland. In the firm level analysis, main control variables include: the technological capability of each foreign R&D facility measuring by the patent stocks on the subunit level, the technological capability of each R&D center measuring by the patent stocks on the division level, and the number of subunits within each innovation center.

6.5. Empirical Results and Discussions

6.5.1 Patent Citation Analysis

Table 30 reports the Pair-Wise correlation matrix of dependent and independent variables. No multicollianarity problem is observed among explanatory variables[14]. Given that in this set of analysis our dependent variables (ITECH-CI), CO-CI, S-CORE and F-CORE are all dichotomous that takes values of one and zero, we used Logistic Regressions to test our hypotheses.

[Insert Table 30 about here]

The regression results are shown in Table 31. Model 1 shows the statistical results for baseline tests. In Model 2, we add GPTs and ICTs as explanatory variables. As defined by the natures of GPTs, patents in the GPTs fields are widely applied in many sectors.

[14] The correlations between Cited-GPT and Cited-GPTs as Supporting Technologies and between Cited_ICT and Cited-ICTs as Supporting Technologies seem high. In our regression tests, we will be careful in using these two variables.

Unsurprisingly, GPTs have a negative and significant coefficient in predicting the Intra-Field Citations. ICTs in this test are positively related to Intra-field Citations. This is also consistent with our expectation in earlier discussion given that many technologies in ICT fields are likely to cite technologies from their own sectors, and thus drive down the generality of GPT fields. Results in Model 3 and Model 5 both show that compared with a MNC or a subsidiary's core technologies, the non-core technologies are less likely to be cited by innovations in the same sector. It implies that the foreign subsidiaries tend to acquire technologies from diversified areas to support the development of their core technologies. The results involving the citations of GPTs are more interesting. Model 4 shows that control for all other factors, GPTs that are used to support the development of the foreign subsidiary's core technologies tend to be cited within the same sector, while GPTs that are peripheral to the core areas of the whole MNC group are likely to have negative intra-field citations. This comparison suggests that patents in GPTs field that are outside the core technology development of the whole MNC group are utilized in a wider range of fields than the GPTs that are to support the subsidiary core technologies.

[Insert Table 31 about here]

In the second set of regressions (Table 32), we firstly try to find out what type of technologies in the MNC foreign subsidiaries that are more likely to cite GPTs. Results in Model 1 and Model 2 show a very interesting comparison. While the core fields of foreign subsidiaries are not likely to cite GPTs controlling for all other factors, these technologies are very likely to be utilized by the innovations in the core areas of the whole MNC group. This finding implies that GPTs are mainly sourced to support the development of a MNC's core technologies, while the subunit's focused activities are relatively independent of using GPTs. A similar result is shown in Model 3. GPTs are more likely to be cited by a foreign subsidiary's core technology field when it is consistent with that of the MNC group's core areas. This finding together with the evidence in intra-field citation activities might help explain the role of GPTs in the formation of what we called the internationally integrated innovation networks of MNCs. In such networks, firms try to build upon their core technologies some supplementary technological competencies with assist of innovations in GPT fields.

[Insert Table 32 about here]

We further look at the co-citations among the cited patents. Model 3 in Table 32 shows the baseline model for co-citations. Regression result in Model 4 suggests that in general patents in GPT fields are less likely to be cited together with other patents. But this is not the case for patents in ICT fields. Moreover, In general, the innovations in the core technology fields of a foreign subsidiary's technology development are more likely to be cited with other patents. Whereas, when the technologies are in the MNC's core areas, they are more likely to be cited alone. The difference in citing core technologies in the host countries illustrates the difference in knowledge acquisitions for MNC subsidiaries. The core technologies for the subsidiaries might be technologically distant from the existing knowledge of the group, and need to be associated with other technologies. However, we didn't find evidence to support our proposition that GPTs are likely to be applied together with other technologies.

Table 33 shows the results of random effect GLS regressions of the diversifications of technological activities of each foreign subsidiary. We distinguish the degree of technological diversification of a firm's innovative activities from the broadening of its technological base (the range of technology fields of cited patents). Model 1 shows that in general there is a negative relationship between GPT creation and the degree of diversification of the firm's technology. We added the variable GPT CIT, which denoted the share of GPT cited by each firm. From results in Model 1 and Model 2, we can't find that GPT is directly related to the foreign subsidiary's diversification. This is consistent with the findings that we obtained in earlier study. Only if GPTs are created and utilized as supporting technologies, they are able to help firm diversify. Model 3 shows some similar results in analyzing the change of structure of a firm's technology base. But interestingly in Model 4 we found that although the development of GPTs in a firm may not be able to help firm diversify their innovation activities, but it might help widening the range of technology opportunities that firms may explore in the future.

[Insert Table 33 about here]

Table 34 shows the logistic regression of citing and cited patents in GPT fields to the development of a MNC and a foreign subsidiary's core technologies. The baseline model (Model 1) shows that in general for MNCs from GPT-based industries, the core technologies developed in their subsidiaries in the U.S tend to differ from that of the MNC group. Model 2 shows that firms that have cited more technologies in GPT fields are more likely to have the subsidiary core technologies differentiated from that of the MNC group. This finding is further supported in Model 3 in which there is a negative relationship between GPT as citing patents and the match between MNC core technology fields and that of the foreign subsidiaries in the U.S. This finding implies that the citations in GPT fields help integrate the knowledge sourced and created in host countries into a firm's own organizational domain. This might imply that the innovation in GPT fields in subsidiary level help the foreign subsidiaries shift away from the original core fields of MNC groups.

[Insert Table 34 about here]

Patent Creation Analysis

The correlation matrix of variables listed in Table 35 and Table 36 show that there are no major multicollinarility problems in our regression models. All dependent variables are normally distributed. To control the firm, subunit and locational heterogeneities, we use both fixed and random-effect GLS regressions.

[Insert Table 35 and Table 36 about here]

Regression results are summarized in Table 37. Model 1 and Model 2 are designed for testing Hypothesis 4a. The GLS regression result in model 1 shows that although the development of GPTs in subunit level in general appears to be negatively associated with the *TechDIV* (degree of technological diversification) of that subunit, when these GPTs are outside a firm's primary fields, they are likely to be positively associated with *TechDIV* in subunit level. This argument is strongly supported controlling for technology stocks and the size of that subunit within MNC groups. We then re-test this proposition by replacing subunit *TechDIV* variable with subunit *TechHHI* which is the degree of technological concentration in each subunit proxied by the Herfindahl Index[15]. Therefore, subunits are becoming more technologically diversified as the *TechHHI* goes down. The result in model 2 helps draw the same conclusion. In particular, although innovative activities across all GPT fields in subunits is positively related to technological specialization. When these GPT-related activities lie outside a firm's primary technology

15 Herfindahl-Hirschman Index or HHI is a concentration ratio calculating as the sum of squares of shares of innovations taken across all technology fields in each subunit.

fields, however, the relationship is negative. In summary, GPTs are playing a role of supporting technologies in corporate technology development, and the efforts in these fields are positively related to the technological diversification in R&D facilities. Hypothesis 1 is strongly supported.

[Insert Table 37 about here]

Hypothesis 4b is supported in model 3. Taking all other factors controlled, GPT innovations among those of all peripheral technologies in a foreign subunit is positively and significantly associated with the share of patents of that subunit in all innovations of the firm in the host country. Again, the GPT development as a whole in a subunit is negatively associated with the former. This finding implies that at least some foreign subsidiaries are becoming more “creative” in terms of technology innovations than others. To explore more technological opportunities in host locations, these subsidiaries need to develop more technologies in GPT fields to support the cross-fertilization of existing knowledge with new inputs.

We further look at the change of the geographical distribution of MNC technology activities in the host country in model 4 and model 5. The result in Model 4 shows that the technological activities in GPT fields in general are likely to be positively associated with the geographical expansion of innovative activities of MNCs, but this relationship is unlikely to be found when these GPTs lie in the primary technological fields. Similarly, Model 5 re-tested this proposition by replacing the diversification (*1/CV*) measurement with Herfindahl Index (*HHI*) of the shares of patents across all subunits in each firm. The result shows a very consistent result. Thus our hypothesis 5 is supported.

Model 6 and model 7 help deepen our understanding on the role of local development of GPTs on the change of regional innovation networks (Hypotheses 6). These two tests are taken in geographical division level. More specifically, it is shown in model 7 that there is a positive association between the GPT development in the secondary fields of all subsidiaries in a given geographical division and the broadness of industrial composition of that innovation center, although the share of GPTs in general is negatively associated with the degree of industrial diversification of that location. This finding is consistent with our proposition that sectoral diversification in certain innovation centers require local development of GPTs as “connectors”, because these generalized technologies are able to ease the cross-sector knowledge diffusion and sharing from different domains. This finding might help explain that some innovative clusters such as Silicon Valley in California and Boston Area in MA which were very concentrated in certain technology fields (Information and Communication technologies) are now becoming more diversified and attracting firms from other industries to agglomerate in these locations.

Finally, the empirical results do not support the hypothesis that the degree of technological diversification of an innovation center tends to be positively associated with local development of GPTs in such locations. We didn’t find a significant relationship between the degree of technological diversification in the geographical division and the non-primary GPTs creation in that location, neither did we find a significant relationship between the technological diversification of the location and the technological diversification of the foreign subunits which are sited in such location. This finding, along with the findings in previous tests suggests that GPTs in non-primary field tend to facilitate knowledge combination across different fields but only within organizational boundaries (within each MNC or within each subsidiary). But such development does improve knowledge sharing across different industries in specific locations.

Chapter 7. Discussions and Conclusions

7.1 Characteristics of GPTs

This dissertation research is based on patents and patent citations, studying the underlying technological trajectory of MNCs, and the change of the structure associated with general trend of globalization in terms of both markets and operations. The patents stocks and patent citations show the accumulation and structural change of a firm's knowledge base.

The comparison of the measurement of GPT fields using patent and patent citations leads to some interesting discussions in our research. Three factors have been emphasized in studying GPTs (Helpman and Trajtenberg, 1998): "1. they are extremely pervasive and used in many sectors of the economy; 2. they are important and are subject to continuous technical advance; and 3. effective use of these technologies requires complementary investment in the using sector". Our first measurement of GPTs using patent stocks translates the three characteristics from an innovation "creation" approach. GPTs are pervasively generated by firms from a wide range of industries. Secondly, they are important given that we only focus on those technologies that have been most innovated (the size of the field). However, the cross-firm approach takes less concern about "complementarity" of GPTs. The cross-field citation-based measurement might be able to illustrate the "diffusion" natures of technologies. This is because patent citations provide a record of the link between present invention and previous inventions. They illustrate both the extent to which a particular narrow technology field has been developed (citing and cited patents are from the same technology field), or whether a particular invention is used in a wide variety of application.

There still exists some inconsistency in defining GPTs using the two approaches. The knowledge creation approach is superior to knowledge application approach in measuring the "importance", which is likely to be ignored by the latter. To illustrate, Miscellaneous Metal Products (Tech 14) have found to be pervasively cited by many other fields (48 in backward citations and 51 in forward citations), and have a fairly high value of GI (0.87 and 0.6, both above the mean). However, the overall size of this technology field is only 2.58%, and thus excluded from GPT groups. Another example is Tech 12 (Pharmaceuticals and Biotechnology). These technologies have been heavily created in the period of study[16]. However, the citation activities in terms of citation generality illustrate a different picture.

However, it is known that using patent data to study innovative activities, especially those of firms is subject to a variety of limitations. It heavily relies on USPTO classification. We only roughly group the technologies into "fields", but are not able to find out the distances between different technology fields. Because of the availability of patent citation data, our period of study is fairly short and not updated. We have experience a high speed growth in new emerging technology fields, such as biotechnologies and information technologies. Moreover, although we've taken into concern the evolution of technology paradigm over year, given time and resource constraint, we could not find out the growth of GPTs (durations or lags of citations). Another difficulty is that patenting in the U.S does not fully reflect improvement in certain industries, such as in software technology. It is because the practice in the USA of protecting software technology through patents is only of recent origin. Also, by using

[16] The highly frequent patenting activities might be driven by the nature of pharmaceutical industry.

patent data, innovations which could not be easily patented are ignored. For instance, with the aids of GPTs and especially ICTs, firms largely improve their production efficiency and supply chain (distribution) system. The role of GPTs from this aspect deserves further studies. Finally, lack of time serious approach might ignore the distorting impact associated with the changes in the strategic uses of patents that have been observed in some high-tech industries (Bessen and Hunt, 2004; Hall, 2005).

Nowadays, products are becoming increasingly diversified in large firms. At this point, the “multi-technology” firms might be “multi-product” in nature. However, it is also known that technologies associated with the production of a single product have dramatically increased. To deliver superior product to customers, firms tend to incorporate technologies from distant fields to build more functions and feature upon existing technologies. We admit that some technologies may serve for a wide range of products, while not for others. In this dissertation, we primarily focus on the upstream activities of firms, more specifically the technology profile of a firm’s knowledge base, with less concern about the commercialization of such technologies. In other words, the possible inconsistency between product and technological diversification is not the focus of this research.

Study I and II provide us a general picture on the geographical distributions of innovation activities in different technology fields. We didn’t find a higher degree of internationalization of innovative activities in GPT fields than that in other fields. This might because GPTs are created to support the technology development in core fields. In early years, all innovative activities are likely to be remained at home countries, so are the GPTs. We also found that compared with other technologies, when GPTs are lying in the core fields of a firm's technology profile, these activities are less likely to be moved abroad. Similarly, firms in GPT-based industries are less likely to have innovative activities in foreign subsidiaries. These findings are consistent with our early discussion that the core technologies are tending to become more geographically dispersed across a wider range of countries over time, so are the GPTs when they outside a firm's core areas. However, the GPTs in general are still likely to be remained at home countries. The latter is possibly driven by the fact that many GPTs lie in the core areas are science-based in character, so the cross-border learning and transfer of some others are much more difficult due to their more tacit natures (Nelson, 1992).

As we have observed in Table 11a and 11b. The focus of innovation activities in GPT fields have started to move from some traditional industrial countries such as U.S, U.K and Germany, to some emerging countries, such as Japan, some small European countries and other East Asian countries (South Korea and Taiwan), which have been actively exploring new technological opportunities in the world. This shift might be explained by the overall structure change of large multinationals. As these firms internationalized their R&D activities, GPTs need to be developed in consistent with this restructure to help firms integrate the knowledge and capabilities that they sourced from foreign countries into their own innovation systems.

7.2 The Role of GPTs in Diversification

The findings in this research suggest GPTs per se might not able to explain the broadening of a firm's technological profile. Only the development of non-core GPTs is positively correlated with a firm's degree of technological diversification and geographical diversification to some extent. This is because corporate technological diversification is close associated with the exploration of new knowledge, skills and process which are not belonging to the firm's existing core fields. As GPTs lie in non-core fields, they are likely to facilitate the combination of existing core technologies and new inputs. However, unlike our expectation, the development of GPTs in core fields is either unrelated or negatively related to corporate diversification. One explanation is that many GPTs such as ICTs are still in a very early stage in their development, and GPT-based firms are not mature enough to expand sectorally and geographically.

Moreover, although many of the inventive activities lie in a firm's core technology fields are still remained at home, there is a trend that increasingly more technological efforts in a firm's core areas have been moved to foreign R&D facilities of MNCs (Cantwell and Janne, 1999; Kuemmerle, 1997; Zander, 1998), to take advantages of local technological specializations. The re-allocation is likely to be accompanied by the reinforced development of GPTs in such host countries. In other words, technological diversification and geographical expansion of large firms are not growth alternatives, but complementary in an evolutionary process given the bridging role of GPTs. The ever broadening technology base of a MNC's subunits might help explain the co-evolution of sectoral diversification and geographical expansion of large multinationals in international market.

7.3 The role of GPTs in the restructuring of MNC international innovation networks

The theoretical rationale for the international integration of R&D activity within the biggest firms is that economic benefits attributable to the more differentiated concentrations in competency exploration in host countries outweigh the costs of national differentiation of demand (Doz, 1986) and being less locally responsive in each market. The multinational company network benefits from economies of locational agglomeration through an interchange with other facilities in the same location and economies of scope through the international intra-firm coordination of related but geographically separated activities.

As argued in our opening remarks, taking more efforts in GPT fields allows MNCs to re-allocate their innovation activities to some selected centers of excellence in accordance with the expertise of those locations. The restructuring consequently enhances the efficiency of the internationally integrated innovation networks. It is often argued in the international business literature that MNCs are facing dual-pressures with one pulling firms towards integration and consistency within an MNC group network, and the other pushing them towards the local embeddedness in their local market (Phene & Almeida, 2003). Amongst large firms, the most successful are those which have developed an efficiently integrated international network (Cantwell and Sanna-Randaccio, 1993). The creation of this cross-border network structure, along with the facilitating role of investment in the GPT and more recently ICT fields as catalysts for new developments in their established areas may allow some firms to grow faster than others.

The findings on the role of GPTs in the change of corporate international innovation networks have implications for a broader understanding of internationalization strategy. In discussions of international strategy, liabilities or advantages of being international have always been in the center of debates. This study suggests that a necessary condition for successful global expansion is to maintain the technological and managerial coherence. Furthermore, many GPTs are science-based, like ICTs. Market for technologies may create incentives for new start-ups and university spin-offs which are R&D specialized to commercialize their GPT-related technologies in local and international market through licensing or forming strategic alliances.

7.4 The role of GPTs on the evolution of some competence-creating subsidiaries

In this research, we propose that in those MNC subsidiaries which bear the competence-creating mandates, there will be increasingly more technological linkages between these subunits with other R&D facilities, and this is facilitated by the local development of technologies in GPT fields. Moreover, the efficiency of knowledge accumulation of these competence-creating subsidiaries in local innovation centers is also improved by the local development of GPTs. This is because GPTs play a bridging role combining the firm's existing technologies with new innovations which are sourced from the host locations. This process is driven both by particularly strong and unique local competencies and by particularly strong company-specific networking capabilities (Cantwell and Santangelo, 1999; Bartlett and Ghoshal, 1989, 1990; Cantwell, 1992).

Therefore, foreign subunits with higher specializations in GPT fields tend to become more technological diversified over time than others, but only when these GPTs are lying in secondary fields for subunits. The shift of innovative efforts to host countries is likely to be accompanied by the reinforced development of GPTs as peripheral technologies in such host countries. The reallocation of a firm's innovative activities to the optimal places will consequently enhance the efficiency of their internationally integrated innovation networks. Building such cross-border networks, along with the reinforcement of innovative efforts in the GPT fields as catalysts for new competency creations lies in the heart of the "advantages of multinationality" of large MNCs. Our findings support and complement theoretical arguments on “Heterarchy” (Hedlund, 1986) model of multinational firms or the concept of “Transnational” MNCs (Bartlett and Ghoshal, 1988; 1990).

Our study also provides more empirical evidences to the existing subsidiary management literature which was primarily focused on the knowledge flows among MNC sub-units (Gupta and Govindarajan, 1991, Birkinshaw and Morrison, 1995, Pearce, 1999). We suggest that in order to balance the dual forces faced by subsidiaries – the internal pull towards integration and consistency within the MNC network and simultaneously an external force towards knowledge sourcing in host countries and regions, many competency-creating subsidiaries are evolving towards a role which act as “local innovator” and “global integrator” simultaneously. Moreover, there tends to be a favorable interaction between the MNC intra-firm innovation network and the regional innovation networks in which the MNC’s foreign subsidiaries are sited. In this process, foreign subsidiaries play a connective role, helping advance and shift the MNC’s core competencies in the long run.

Moreover, the knowledge accumulation in most MNC’s foreign subsidiaries is a dual process. On the one hand, subsidiaries need to be embedded in local networks to source new competencies. On the other hand, they need to be integrated within the MNC intra-firm networks to leverage more existing competencies. Subsidiaries are differentiated according to their technological capabilities and roles (Ghoshal and Bartlett, 1998). Those that are primarily focused on “creating” and “searching” (Gupta and Govindarajan, 1991) are taking innovative activities which are distant from the existing core areas of the rest of the MNC group, and are thus relatively more independent. These subsidiaries are more likely to create GPTs to support the new innovations. While those that are mainly taking the role of implementer" or "bearing the world mandate" (Birkinshaw and Morrison, 1995) are more interrelated with the existing technological expertise of MNC group.

As we have discussed in previous chapters, the core technologies developed in foreign subsidiaries differ in their connectedness with the primary fields of the whole MNC group. GPTs are mainly cited to support the creations of MNC's core fields. Therefore, when a subsidiary's core fields match that of other parts of the MNC group's, they need to cite more GPTs. This type of foreign subsidiaries is more likely to be defined as the global integrator or bearing a world mandate. Contrarily, if a subsidiary's core activities are less connected with MNC group's core areas, less GPTs will be cited. This explains why we found in study II that the creation of GPTs in a foreign subsidiary is associated with the creation of core capabilities in that subsidiary.

The creation of GPTs, however, helps enhance a subsidiary's absorptive capacity, which allow the subsidiary to acquire and assimilate knowledge from other actors within the local network in host country. This type of subsidiaries maintains only a weak connection with its MNC group, and its technology developments aren't necessarily following the path of the whole MNC network. The creation of distant technology capabilities needs less assist of GPTs. A possible explanation is that the creation of knowledge that is less interrelated to the existing core areas of the MNC group is more likely to be associated with the local expertise and thus less likely relies on GPTs to combine them.

Another interesting finding is that GPTs are active in broadening the knowledge base and industrial diversity of local innovation clusters in which the subsidiaries are located. Silicon Valley is a salient example. In this area, computer system manufacturers relied on networks of independent suppliers who specialized in incorporating the latest technological advances into modular components (Saxenian, 2000). This modularized technology model offered great opportunities for further technological development and cross-sectoral applications (Kenney and Von Burg, 1999). Moreover, only a few locations with proper technological expertise are able to embrace and develop new technologies (Vertova, 2002).

Local systems interplay with the international dispersion of the creation of new technology, and the latter has been associated with a restructure in MNC innovatory strategies, that is, to increase its global technological advantage from certain foreign sources. Therefore, GPTs facilitate a more favorable interaction between knowledge seeking activities of MNC foreign subsidiaries and local knowledge stocks. As subsidiaries that absorb more knowledge locally are also most likely to share it with other units (Almeida, 1996), the regional innovation system tends to interact with the MNC intra-firm innovation network by sharing knowledge among their subunits.

Table 1. Changes of technological structure of Boeing's R&Ds (1969 – 1995)

T	Description	P1	P2	P3	P4	P5	P6
1	food and tobacco product		0.28%				
3	inorganic chemicals					0.27%	
5	chemical processes	3.35%	4.19%	5.44%	5.16%	6.85%	4.41%
6	photographic chemistry						0.61%
7	cleaning agents & other compositions	1.44%	0.56%		0.19%	0.13%	1.07%
8	disinfectants & preservatives		0.28%				
9	synthetic resins and fibers	0.48%	1.12%	0.39%	0.76%	1.34%	3.81%
10	bleaching and dyeing			0.19%			
11	other organic compounds					0.40%	1.07%
12	pharmaceuticals and biotechnology	0.96%	0.28%	0.39%		0.13%	
13	metallurgical processes	4.31%	3.63%	3.88%	2.49%	4.17%	6.24%
14	miscellaneous metal products	5.26%	4.75%	6.80%	5.93%	4.03%	3.20%
16	chemical and allied equipment	1.91%	1.96%	1.36%	2.87%	1.75%	1.67%
17	metal working equipment	3.35%	7.26%	4.66%	5.74%	3.90%	5.63%
18	paper making apparatus		0.28%				
19	building material handling equipment				0.19%		
20	assembly and material handle equipment	3.35%	2.51%	2.52%	3.82%	2.55%	1.67%
23	Mining equipment				0.19%		
25	Textile and clothing machinery					0.13%	0.15%
26	Printing and publishing machinery		0.28%			0.13%	
27	Woodworking tools and machinery					0.13%	
28	Other specialized machinery	0.48%	0.28%	1.36%	1.53%	3.09%	1.52%
29	other general industrial equipment	11.48%	8.38%	8.35%	6.50%	5.65%	3.81%
30	mechanical calculators and typewriters		0.28%				
31	power plants	2.39%	2.79%	4.85%	1.72%	2.28%	2.59%
33	Telecommunications	1.91%	0.84%	1.17%	0.57%	2.15%	1.52%
34	Other electrical communication system	3.35%	1.12%	1.17%	0.38%	2.82%	1.67%
35	Special radio system	2.87%	2.23%	2.33%	4.21%	3.63%	5.18%
36	Image and sound equipment	2.87%	1.68%	2.14%	1.53%	0.81%	0.30%
37	Illumination devices	0.96%	0.56%	0.58%	0.96%	0.27%	
38	Electrical devices and systems	2.39%	2.51%	3.88%	3.82%	4.84%	3.50%
39	Other general electrical equipment	1.44%	2.79%	4.08%	3.06%	2.96%	4.41%
40	semiconductor	0.96%	1.40%	0.19%		0.27%	0.76%
41	Office equipment	2.87%	2.23%	4.66%	6.31%	7.26%	10.65%
42	internal combustion engines				0.19%		
43	motor vehicles	0.48%			0.19%		
44	aircraft	16.27%	28.21%	19.22%	21.61%	17.34%	14.76%
45	ships and marine propulsion	0.48%	5.03%	1.94%	1.15%		
46	railways and railway equipment		0.84%	0.39%	0.19%	0.13%	
47	other transport equipment		0.56%	0.58%		0.54%	0.15%
49	Rubber and plastic products		0.56%	0.39%	1.53%	0.81%	0.91%
50	non-metallic mineral products	2.39%	2.51%	2.33%	5.93%	3.09%	3.50%
51	coal and petroleum products	0.48%					
52	photographic equipment	0.48%		0.19%			
53	Other instruments and controls	19.14%	6.42%	12.82%	8.60%	13.84%	13.55%
54	Wood products	0.96%		0.58%	0.57%	0.40%	0.15%
56	Other manufacturing and non-industrial	0.96%	1.40%	1.17%	2.10%	1.88%	1.52%
	Total	1	1	1	1	1	1

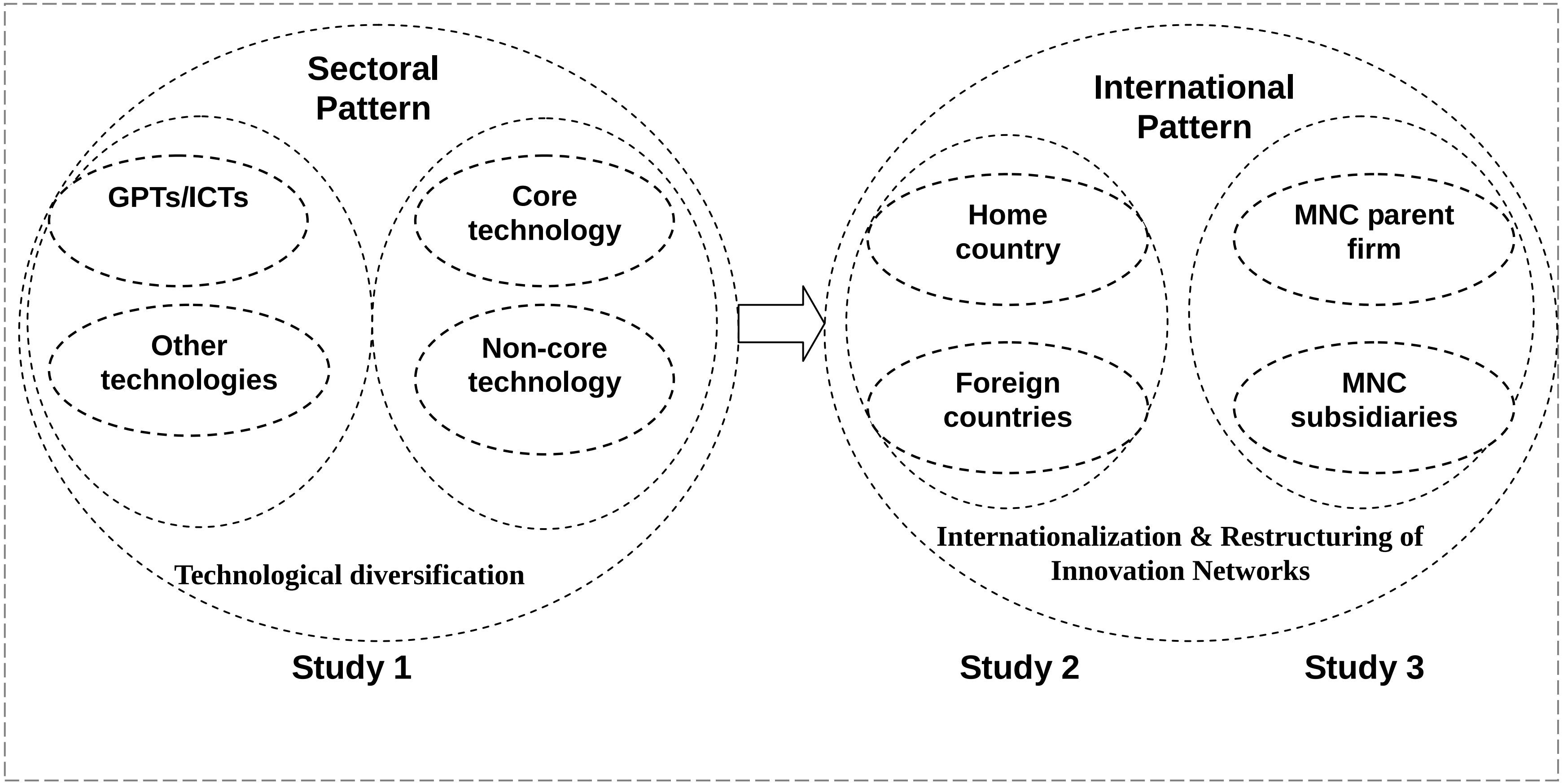


Figure 1. General Research Framework

Table 2. The primary technology field(s) of each industrial group.

Industry	Primary Technology Fields
Food, drink and tobacco	1,15
Chemicals	2,3,4,5,7,8,9,10,11,16,55
Pharmaceuticals	12
Metals	13,14,17
Mechanical engineering	20,21,22,28,29
Electrical equipment	24,32,33,34,35,36,37,38,39,40
Office equipment	**30,41**
Motor vehicle	42,43,47
Aircraft and other transport equipment	44,31, 45, 46
Textile	25,48
Paper products, printing and publishing	18,26,27
Rubber products	49
Non-metallic mineral products	19,50
Coal and petroleum products	23,51
Professional and scientific instruments	**6,52,53**
Other manufacturing	54,56

Notes: For the descriptions of each technology field, please refer to Table 3.

Table 3. The description of 56 technological fields

Tech	Technological Fields	Tech	Technological Fields
1	food and tobacco product	29	other general industrial equipment
2	distillation processes	30	mechanical calculators and typewriters
3	inorganic chemicals	31	power plants
4	agricultural chemicals	32	nuclear reactors
5	chemical processes	33	telecommunications
6	photographic chemistry	34	other electrical communication systems
7	cleaning agents & other compositions	35	special radio system
8	disinfectants & preservatives	36	image and sound equipment
9	synthetic resins and fibers	37	illumination devices
10	bleaching and dyeing	38	electrical devices and systems
11	other organic compounds	39	other general electrical equipment
12	pharmaceuticals and biotechnology	40	semiconductors
13	metallurgical processes	41	office equipment
14	miscellaneous metal products	42	internal combustion engines
15	food drink and tobacco equipment	43	motor vehicles
16	chemical and allied equipment	44	aircraft
17	metal working equipment	45	ships and marine propulsion
18	paper making apparatus	46	railways and railway equipment
19	building material handling equipment	47	other transport equipment
20	assembly and material handling equipment	48	textile, clothing and leather
21	agricultural equipment	49	rubber and plastic products
22	other construction and excavating equipment	50	non-metallic mineral products
23	mining equipment	51	coal and petroleum products
24	electrical lamp manufacturing	52	photographic equipment
25	textile and clothing machinery	53	other instruments and controls
26	printing and publishing machinery	54	wood products
27	woodworking tools and machinery	55	explosives, compositions and charges
28	other specialized machinery	56	other manufacturing and non-industrial

Table 4. The description of 16 industries according to the main outputs

Industry	Industries of Corporate Output	Period1	Period 2	Period 3
1	Food, drink and tobacco	2.20%	1.80%	1.43%
4	Chemicals	20.07%	18.50%	17.30%
5	Pharmaceuticals	7.23%	7.03%	5.59%
6	Metals	5.49%	5.06%	3.94%
7	Mechanical engineering	6.56%	6.04%	3.37%
8	Electrical equipment	21.49%	23.24%	29.49%
9	Office equipment	6.12%	6.06%	8.04%
10	Motor vehicle	7.33%	8.79%	8.85%
11	Aircraft and other transport equipment	5.31%	4.89%	4.97%
13	Textile	0.60%	0.72%	0.66%
14	Paper products, printing and publishing	0.60%	1.29%	1.19%
16	Rubber products	1.59%	1.21%	0.93%
17	Non-metallic mineral products	2.51%	2.03%	1.54%
18	Coal and petroleum products	7.68%	7.57%	5.31%
19	Professional and scientific instruments	3.17%	4.34%	6.74%
20	Other manufacturing	1.48%	1.40%	0.65%

Table 5a. The number of the patents in j industry and I technological field

Tech	Ind	Ind1	Ind2	.	.	.	.	Ind16	Total
Tech 1		P_{11}	p_{21}						$B_1 = \sum_{j=1}^{16} x_j y_1 = \sum_{j=1}^{16} p_{1j}$
Tech 2		p_{12}							
.		.	.						
.		.	.						
Tech 56								p_{ij}	
Total		$A_1 = x_1 \sum_{i=1}^{56} y_i = \sum_{i=1}^{56} p_{i1}$							$Total_p = \sum_{i=1}^{56} \sum_{j=1}^{16} x_j y_i = \sum_{i=1}^{56} \sum_{j=1}^{16} P_{ij}$

p_{ij} denotes the number of patents in industry *j* and technological field *i*

Table 5b. The share of technology fields in each industry

Tech	Ind	Ind1	Ind2	.	.	.	.	Ind16	Total
Tech 1		$P_{ij} / \sum_j P_{ij}$							100%
Tech 2									100%
.									100%
.									100%
Tech 56									100%
Total									

Table 5c. The share of industries in each technology field (Ind_Tech)

Tech	Ind	Ind1	Ind2	.	.	.	.	Ind16	Total
Tech 1		$P_{ij} / \sum_i P_{ij}$							
Tech 2									
.									
.									
Tech 56									
Total		100%	100%	100%	100%	100%	100%	100%	100%

Table 6. The Classification of General Purpose Technology Fields

Tech 56	shares	share above average (3.32%)	Tech 56	shares	share above average (3.32%)	Tech 56	shares	share above average (3.32%)
1	0.81%	1	20	1.81%	3	39	4.62%	7
2	0.15%	0	21	0.30%	1	40	1.98%	2
3	1.03%	1	22	0.06%	0	41	5.89%	6
4	0.57%	0	23	0.93%	3	42	1.51%	1
5	3.97%	9	24	0.10%	0	43	0.62%	1
6	2.17%	4	25	0.62%	1	44	0.29%	1
7	2.34%	4	26	0.31%	0	45	0.16%	0
8	0.04%	0	27	0.04%	0	46	0.20%	0
9	5.68%	8	28	1.66%	4	47	0.58%	1
10	0.41%	0	29	4.73%	7	48	0.06%	0
11	7.79%	7	30	0.33%	0	49	1.17%	2
12	4.31%	5	31	0.89%	2	50	3.24%	6
13	2.43%	3	32	0.33%	0	51	1.48%	2
14	2.58%	8	33	2.32%	2	52	1.81%	2
15	0.11%	0	34	1.50%	1	53	8.69%	17
16	3.32%	10	35	0.57%	0	54	0.16%	0
17	1.93%	3	36	2.27%	3	55	0.08%	0
18	0.69%	1	37	1.42%	1	56	0.99%	1
19	0.19%	0	38	5.76%	7			

Table 7. Historical growth of GPT fields over time

Tech. Field	period1	period2	period3
5 Chemical Process	4.01%	4.30%	3.68%
9 Synthetic resins and fibers	5.76%	6.03%	5.34%
11 Other organic compounds	11.52%	7.50%	4.97%
16 Chemical and allied equipment	3.56%	3.66%	2.87%
29 Other general industrial equipment	5.37%	4.94%	4.04%
38 Electrical devices and systems	6.11%	5.40%	5.75%
39 Other general electrical equipment	4.43%	4.73%	4.68%
41 Office equipment	3.21%	4.74%	8.94%
53 Other instruments and controls	7.18%	8.20%	10.30%

Table 8a. citation analysis on GPTs fields defined by technology creation approach

Tech	Backward # of citations	Forward # of citing patents		Backward # of citations	Forward # of citing patents
1	7.51	1.32	**29**	7.67	1.23
2	6.93	1.54	**30**	9.71	1.10
3	6.80	1.64	**31**	8.51	1.31
4	5.35	1.54	**32**	6.90	1.27
5	7.99	1.52	**33**	6.62	1.28
6	8.93	2.02	**34**	6.33	1.24
7	8.62	1.86	**35**	8.66	1.22
8	8.65	1.68	**36**	6.90	1.43
9	7.92	2.08	**37**	5.48	1.29
10	6.45	1.42	**38**	6.39	1.23
11	4.59	1.78	**39**	7.51	1.38
12	6.43	2.32	**40**	6.28	1.40
13	6.93	1.38	**41**	7.48	1.35
14	8.77	1.21	**42**	9.60	1.39
15	6.07	1.19	**43**	7.91	1.38
16	8.64	1.57	**44**	6.69	1.11
17	7.98	1.27	**45**	7.72	1.36
18	9.80	1.65	**46**	5.83	1.14
19	5.28	1.21	**47**	5.92	1.25
20	8.27	1.22	**48**	4.70	1.33
21	7.70	1.27	**49**	10.28	1.59
22	8.50	1.08	**50**	8.79	1.52
23	13.19	2.13	**51**	10.04	1.82
24	4.91	1.32	**52**	7.16	1.17
25	9.25	1.47	**53**	8.35	1.62
26	10.83	1.41	**54**	8.79	1.09
27	7.71	1.27	**55**	12.60	1.17
28	8.23	1.33	**56**	9.66	1.64

This analysis is based on patents created by all non-U.S firms in the U.S from 1969 to 1995 and all citations of these patents.

Table 8b. Citation analysis on GPTs fields defined by technology creation approach (adjusted by dropping patents with very few citations)

Tech	Backward # of citations	Forward # of citing patents		Backward # of citations	Forward # of citing patents
1	13.20	2.44	**29**	13.01	2.48
2	10.47	3.01	**30**	12.09	2.11
3	12.26	3.18	**31**	13.75	3.08
4	14.41	2.79	**32**	9.80	2.65
5	13.88	2.97	**33**	13.13	2.47
6	13.78	3.75	**34**	11.68	2.38
7	13.80	3.32	**35**	14.28	2.46
8	13.60	3.00	**36**	12.57	2.83
9	14.33	3.68	**37**	10.29	2.47
10	10.98	2.56	**38**	13.32	2.40
11	13.01	3.22	**39**	12.74	2.76
12	14.94	4.32	**40**	11.53	2.59
13	13.09	2.60	**41**	13.19	2.53
14	13.48	2.42	**42**	14.34	2.75
15	12.78	2.38	**43**	14.80	2.77
16	14.44	3.29	**44**	15.00	2.00
17	13.89	2.58	**45**	11.83	2.85
18	15.61	3.04	**46**	10.18	2.85
19	9.80	2.50	**47**	11.73	2.72
20	14.67	2.32	**48**	9.00	2.91
21	12.89	2.43	**49**	15.66	2.99
22	9.38	2.13	**50**	14.48	2.93
23	19.99	4.17	**51**	16.70	3.30
24	10.67	2.46	**52**	11.30	2.35
25	13.68	2.74	**53**	15.40	3.63
26	14.84	2.77	**54**	12.00	2.23
27	18.50	2.00	**55**	26.00	2.22
28	13.48	2.76	**56**	15.12	3.84

Table 9. Classification of GPT fields from a technology application approach

Tech	Backward # of cited fields	Backward Generality Index	Forward # of citing fields	Forward Generality Index
1	27	0.8317	24	0.5209
2	10	0.7950	19	0.6514
3	29	0.8526	30	0.7218
4	23	0.7902	20	0.6024
5	55	0.8974	51	0.7778
6	28	0.7899	26	0.4508
7	47	0.8711	39	0.6826
8	22	0.8995	19	0.8584
9	49	0.7950	39	0.4664
10	24	0.8621	21	0.7153
11	40	0.8227	32	0.6576
12	47	0.7928	30	0.4102
13	44	0.8690	43	0.6836
14	48	0.8696	51	0.6060
15	19	0.9210	20	0.7881
16	53	0.8932	49	0.7222
17	39	0.8706	45	0.6503
18	43	0.8739	35	0.5621
19	17	0.8860	23	0.8151
20	40	0.8762	48	0.5291
21	17	0.7974	23	0.2268
22	8	0.8367	16	0.7221
23	36	0.8754	29	0.4039
24	12	0.8145	12	0.6781
25	28	0.9005	25	0.4916
26	28	0.8959	29	0.6133
27	9	0.8600	10	0.6774
28	44	0.8797	52	0.6958
29	46	0.8629	52	0.6095
30	19	0.8646	22	0.5809
31	34	0.8539	29	0.6703
32	12	0.8249	17	0.6960
33	34	0.8045	29	0.4814
34	36	0.8427	37	0.7378
35	18	0.8393	18	0.6460
36	31	0.7570	37	0.3940
37	28	0.6740	30	0.4141
38	39	0.7858	41	0.5350
39	50	0.8547	47	0.6180
40	29	0.7960	24	0.6226
41	43	0.7317	41	0.3673
42	24	0.8196	24	0.3999
43	24	0.8232	31	0.5808
44	12	0.8673	21	0.8140
45	27	0.8602	21	0.5525
46	15	0.7979	20	0.5060
47	22	0.8469	30	0.7283
48	8	0.7872	16	0.6264
49	39	0.9052	44	0.8123
50	52	0.8958	46	0.7816
51	31	0.8444	30	0.5345
52	24	0.8717	24	0.6964

53	54	0.8404	52	0.4948
54	13	0.8721	18	0.5492
55	9	0.9620	14	0.7711
56	41	0.8785	45	0.6681

(This analysis is based on patents created by all non-U.S firms in the U.S from 1969 to 1995 and all citations of these patents)

Table 10. The comparison of classifications of GPT fields using cross-industry and cross-field approaches

	Cross-Industry Creation		Cross-field Application	
GPT Fields	**Pervasiveness**	**Importance**	**Pervasiveness**	**Importance**
5 Chemical Process	medium	high	High	high
9 Synthetic resins and fibers	High	high	High	Medium
11 Other organic compounds	High	high	Medium	high
16 Chemical and allied equipment	High	medium	High	high
29 Other general industrial equipment	Low	high	High	high
38 Electrical devices and systems	high	high	Medium	Medium
39 Other general electrical equipment	Medium	high	High	High
41 Office equipment	High	high	High	low
50 Non-metallic mineral products	Low	medium	High	High
53 Other instruments and controls	High	Very high	High	high

Table 11. The Distribution of Innovations in GPT fields across Home Countries

	Patents	Share	Foreign Share	Foreign Share	Foreign Share	Non-core GPT foreign share	Non-core GPT foreign share	Non-core GPT foreign share
1 U.S	518831	54.72%	5.42%	6.92%	8.32%	5.59%	6.15%	7.11%
2 Germany	90037	9.50%	11.70%	13.18%	19.00%	6.59%	12.88%	19.90%
3 UK	43235	4.56%	42.12%	43.41%	52.97%	45.51%	51.58%	66.90%
4 Italy	5230	0.55%	14.93%	13.32%	13.52%	12.62%	8.70%	21.62%
5 France	24949	2.63%	7.90%	8.14%	26.94%	9.34%	8.55%	25.32%
6 Japan	199699	21.06%	2.10%	1.24%	1.02%	1.74%	1.09%	1.00%
7 Netherlands	18300	1.93%	48.60%	50.79%	54.80%	45.98%	46.78%	49.46%
8 Belgium	1383	0.15%	53.03%	63.54%	61.11%	41.76%	59.70%	31.03%
9 Switzerland	23307	2.46%	43.90%	42.88%	47.71%	55.48%	53.48%	44.18%
10 Sweden	10984	1.16%	19.07%	27.51%	36.50%	18.14%	25.79%	42.10%
13 Spain	10	0.00%	75.00%	33.33%	0. 00%	75.00%	100.00%	0. 00%
15 Luxembourg	309	0.03%	28.57%	22.78%	15.52%	37.50%	33.33%	39.13%
17 Austria	932	0.10%	13.10%	16.26%	7.11%	11.11%	34.19%	2.04%
18 Norway	374	0.04%	4.29%	23.45%	27.67%	0. 00%	16.67%	48.00%
19 Finland	1326	0.14%	25.11%	22.52%	33.49%	31.58%	25.56%	30.79%
27 Canada	5304	0.56%	40.07%	37.71%	42.14%	36.86%	30.87%	39.37%
28 Australia	327	0.03%	27.17%	34.15%	14.29%	20.00%	22.58%	7.14%
29 New Zealand	29	0.00%	80.00%	40.00%	92.86%	100.00%	50.00%	0. 00%
38 Panama	1095	0.12%	99.58%	100.00%	100.00%	99.45%	100.00%	100.00%
42South Korea	2361	0.25%	0. 00%	15.38%	2.85%	0. 00%	33.33%	1.88%
43 Taiwan	27	0.00%	0. 00%	28.57%	65.00%	0. 00%	0. 00%	76.92%
Others		0.01%	-	-	-	-	-	-
Total		100%	-	-	-	-	-	-

Table 12. Innovative activities across all industries in each innovation center

ind	1	2	3	4	5	6	7	8	9	Total
1	2.79%	36.02%	17.87%	1.34%	17.20%	11.62%	5.76%	2.21%	5.19%	100%
4	8.99%	29.88%	19.39%	2.18%	18.08%	1.97%	3.86%	1.29%	14.36%	100%
5	6.28%	**43.44%**	13.89%	5.28%	9.46%	1.16%	1.55%	4.11%	14.82%	100%
6	12.13%	26.75%	15.69%	6.78%	17.05%	1.57%	4.35%	0.93%	14.76%	100%
7	17.41%	20.95%	33.30%	6.98%	8.30%	1.52%	5.57%	0.91%	5.06%	100%
8	7.27%	22.19%	24.63%	1.37%	10.36%	2.37%	4.90%	3.12%	23.78%	100%
9	15.88%	18.77%	5.05%	1.08%	1.08%	0.36%	5.42%	7.22%	**45.13%**	100%
10	4.45%	10.49%	36.09%	18.12%	8.74%	0.64%	0.95%	2.70%	17.81%	100%
11	14.63%	7.32%	7.32%	2.44%	**46.34%**	0.00%	0.00%	9.76%	12.20%	100%
12	27.27%	9.09%	**54.55%**	0.00%	0.00%	0.00%	0.00%	0.00%	9.09%	100%
13	14.05%	35.54%	14.88%	0.83%	23.97%	2.48%	4.13%	0.00%	4.13%	100%
14	8.87%	47.01%	10.31%	2.47%	5.98%	0.21%	11.96%	2.68%	10.52%	100%
16	8.33%	33.33%	36.90%	0.00%	13.10%	3.57%	0.00%	2.38%	2.38%	100%
17	3.64%	37.25%	9.31%	9.31%	17.00%	5.26%	3.64%	1.62%	12.96%	100%
18	8.49%	18.18%	18.41%	1.99%	3.29%	1.02%	**30.29%**	4.92%	13.40%	100%
19	16.54%	30.08%	7.52%	0.75%	11.28%	0.00%	6.02%	3.01%	24.81%	100%
20	15.75%	13.01%	34.93%	3.42%	10.27%	4.79%	4.11%	0.00%	13.70%	100%
GPT innovations in the primary fields of a firm										
Primary coefficient	.1029+	-.0379+	-.0683+	.0326	.1616	.0189	.2873+	.0289	.1029+	

+ $p < .01$

Area 1 (Northeast)

Division 1 (New England) Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut

Division 2 (Mid-Atlantic) New York, Pennsylvania, New Jersey,

Area 2 (Midwest)

Division 3 (East North Central) Wisconsin, Michigan, Illinois, Indiana, Ohio

Division 4 (West North Central) Missouri, North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa

Area 3 (South)

Division 5 (South Atlantic) Delaware, Maryland, District of Columbia, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida

Division 6 (East South Central) Kentucky, Tennessee, Mississippi, Alabama

Division 7 (West South Central) Oklahoma, Texas, Arkansas, Louisiana

Area 4 (West)

Division 8 (Mountain) Idaho, Montana, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico

Division 9 (Pacific) Alaska, Washington, Oregon, California, Hawaii

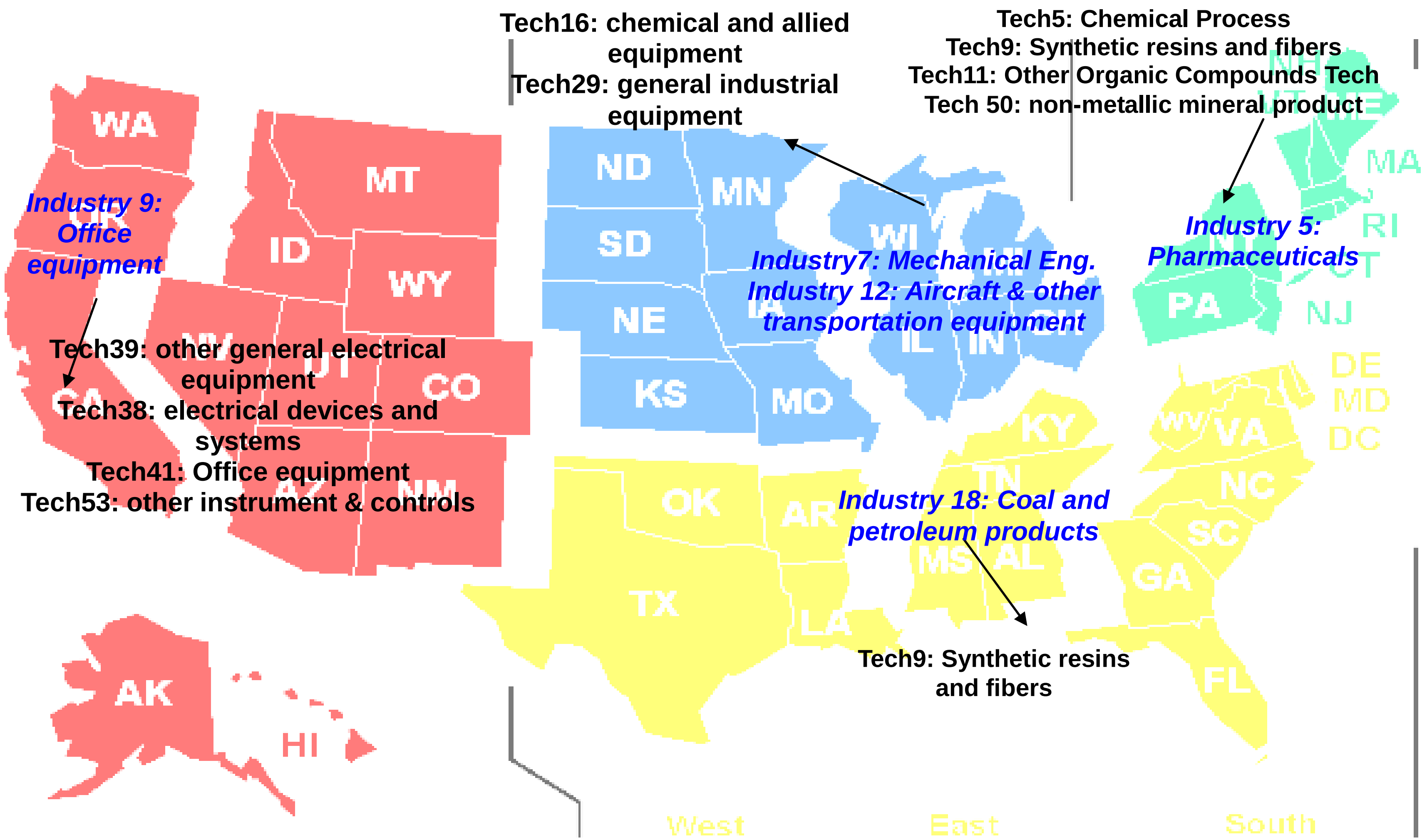


Figure 2. Distribution of innovative activities by foreign firms in the U.S according to nine CBDs.

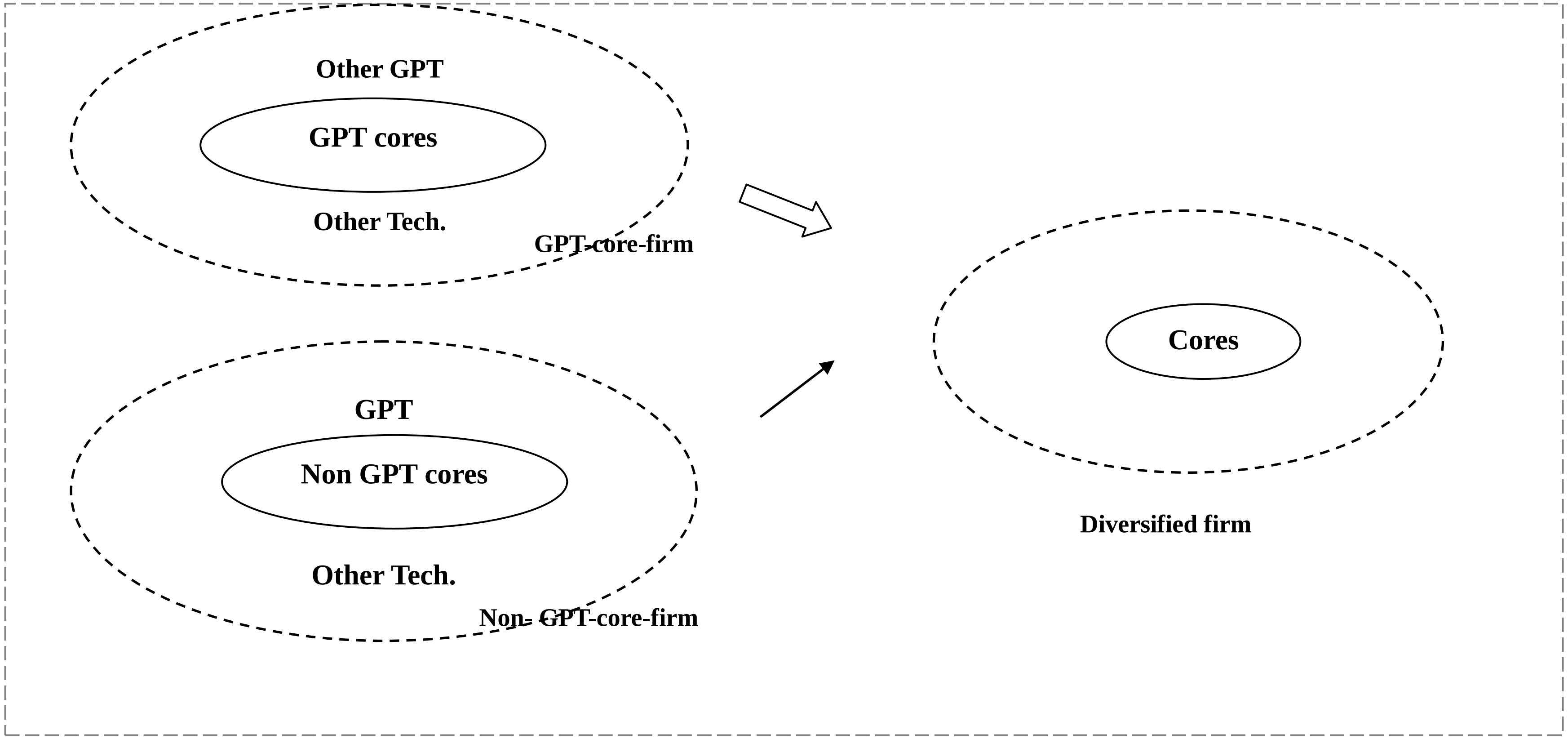


Figure 3. Empirical Model for Study I

Table 13. The primary technology field(s) of each industrial group and the change of their shares.

Industry	Primary Technology Fields	The share of primary tech. field(s)		
		Period 1	**Period 2**	**Period 3**
Food, drink and tobacco	1,15	27.74%	28.46%	26.06%
Chemicals	2,3,4,5,7,8,9,10,11,16,55	57.77%	59.35%	53.91%
Pharmaceuticals	12	18.35%	34.78	44.25%
Metals	13,14,17	29.19%	28.00%	25.37%
Mechanical engineering	20,21,22,28,29	29.56%	25.24%	21.56%
Electrical equipment	24,32,33,34,35,36,37,38,39,40	52.97%	49.51%	48.90%
Office equipment	**30,41**	21.28%	26.81%	29.60%
Motor vehicle	42,43,47	16.07%	27.90%	23.81%
Aircraft and other transport equipment	44,31, 45, 46	18.92%	19.22%	18.36%
Textile	25,48	17.78%	9.94%	5.39%
Paper products, printing and publishing	18,26,27	20.64%	21.48%	19.40%
Rubber products	49	12.63%	19.11%	20.81
Non-metallic mineral products	19,50	21.86%	23.7%	19.12%
Coal and petroleum products	23,51	14.34%	15.25%	14.73%
Professional and scientific instruments	**6,52,53**	59.05%	59.14%	51.62%
Other manufacturing	54,56	11.14%	8.28%	9.76%

Notes: For the descriptions of each technology field, please refer to Table 3.

Table 14. Correlations (obs=51)

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
P_IND_SHARE	.7341	.1559	1.0000										
IND_DIV	.8459	.1781	.4643	1.0000									
GPTs	.4358	.0917	-.2145	-.2541	1.0000								
ICT	.1117	.0947	-.2527	-.1183	.3873	1.0000							
GPT_SUPP	.5062	.1290	.0183	-.1837	.2971	.0722	1.0000						
ICT_SUPP	.1259	.0962	-.3097	.0722	.3347	.5922	.2091	1.0000					
GPT_IND	.2941	.4601	-.7003	-.1241	.4144	.5592	-.3692	.4141	1.0000				
ICT_IND	.1176	.3253	-.3470	-.2918	.2755	.7969	-.0583	.0645	.5657	1.0000			
IND_TOTAL	18591.71	21288.08	-.6547	-.1264	.5590	.2933	.0135	.7360	.6030	-.0005	1.0000		
IND	11.1764	5.5234	.3027	.1017	-.0416	.1492	.1833	-.1015	-.2097	.1885	-.3655	1.0000	
PERIOD	2	.8246	.0027	.0657	-.0439	.1783	-.0080	.2272	.0000	.0000	.0775	-.0000	1.0000

Table 15. Regression Results of the share of primary fields in each industry

Variables	Model 1 P_IND_Share	Model 2 P_IND_Share	Model 3 P_IND_Share	Model 4 P_IND_Share	Model 5 P_IND_Share
Constant	.7832***	.5432***	.5642***	.7784***	.7579***
I.V					
GPTs		.6334**	.6696***		
GPT_SUPP			-.0724*		
ICT				1.2472**8	2.7255***
ICT_SUPP					-1.2468**
GPT_IND	-.1028*	-.0736	-.0935	-.0605	-.0461
ICT_IND	-.0949	-.1638**	-.1528*	-.4109***	-.7748
Control Variables					
IND_SIZE	.0000**	.0000***	.0000***	-.0000***	-.0000**
INDUSTRY	.0034	.0022	.0023	.0011	.0021
PERIOD	.0068	.0140	.0137	-.0140	-.0155
R-sq	.5995	.6791	.6810	.7337	.7773
Adjusted R-sq	.5550	.6353	.6291	.6973	.7411
F value	13.47	15.52	13.11	20.2	21.44
N. of obs.	51	51	51	51	51

+ $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

Table 16. Regression Results of degree of technological diversification of each industry

Variables	Model 1 IND-DIV	Model 2 IND-DIV	Model 3 IND-DIV	Model 4 IND-DIV	Model 5 IND-DIV
Constant	.7801***	.8834***	.8723***	.8704***	.9508***
Independent Variables					
GPTs		-.2726	-.2552		
GPT_SUPP				-.1886	-.3331
ICT			1.1839**		
ICT_SUPP					.9431**
GPT_IND	.1702*	.1576	.1985**	.1139	.0977
ICT_IND	-.3146**	-.2850**	-.5869***	-.2756**	-.2767**
Control Variables					
IND_TOTAL	-.0000	-.0000	-.0000**	.0000	-.0000**
IND	.0058	.0063	.0042	.0063	.0040
PERIOD	.0198	.0167	-.0029	.0179	-.0011
R-sq	.1795	.0198	.2834	.1908	.2859
Adjusted R-sq	.0884	.0805	.1667	0.0805	.1697
F value	1.97	1.73	2.43	1.73	2.46
N. of observations	51	51	51	51	51

+ $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

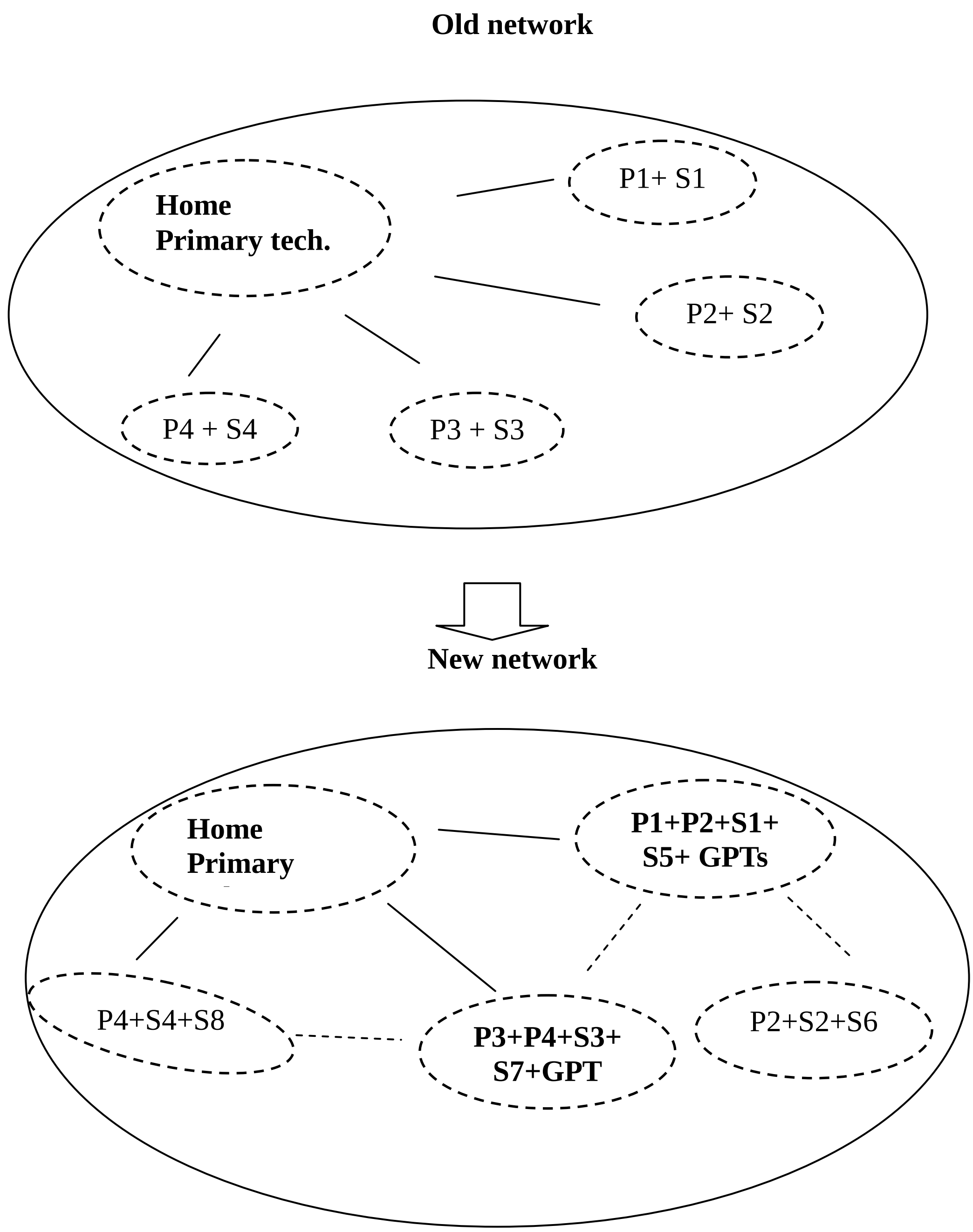


Figure 4. The evolutionary international innovation network within MNC

Table 17. The numbers of MNC groups and subunits across all home countries in each period

	Patents		Industry-Country					Industry-Country-Host				
	Patents	Share	P1	P2	P3	Total	Percentage	P1	P2	P3	Total	Percentage
USA	518831	54.72%	17	17	17	51	11.41%	223	190	205	618	30.37%
Germany	90037	9.50%	15	14	13	42	9.40%	64	64	67	195	9.58%
UK	43235	4.56%	17	17	17	51	11.41%	94	90	81	265	13.02%
Italy	5230	0.55%	8	8	8	24	5.37%	18	16	18	52	2.56%
France	24949	2.63%	14	14	13	41	9.17%	56	47	58	161	7.91%
Japan	199699	21.06%	16	16	16	48	10.74%	39	35	46	120	5.9%
Netherlands	18300	1.93%	4	4	4	12	2.68%	24	22	19	65	3.19%
Belgium	1383	0.15%	3	3	3	9	2.01%	9	10	8	27	1.33%
Switzerland	23307	2.46%	8	8	8	24	5.37%	50	57	41	148	7.27%
Sweden	10984	1.16%	11	11	11	33	7.38%	52	56	54	162	7.96%
Spain	10	0.00%	2	2	1	5	1.12%	2	1	1	4	0.2%
Luxembourg	309	0.03%	1	1	1	3	0.67%	3	3	4	10	0.49%
Austria	932	0.10%	3	3	3	9	2.01%	4	6	3	13	0.64%
Norway	374	0.04%	2	2	2	6	1.34%	2	3	8	13	0.64%
Finland	1326	0.14%	5	5	5	15	3.36%	11	13	14	38	1.87%
Canada	5304	0.56%	9	9	8	26	5.82%	29	27	25	81	3.98%
Australia	327	0.03%	5	5	4	14	3.13%	6	7	5	18	0.88%
New Zealand	29	0.00%	1	1	1	3	0.67%	1	2	0	3	0.15%
Brazil	76	0.01%	1	1	1	3	0.67%	1	1	1	3	0.15%
Israel	8	0.00%	1	1	1	3	0.67%	0	1	0	1	0.05%
Chile	1	0.00%	0	1	0	1	0.22%	0	1	0	1	0.05%
Mexico	3	0.00%	0	1	0	1	0.22%	0	0	0	0	0.00%
Panama	1095	0.12%	1	1	1	3	0.67%	7	3	3	13	0.64%
South Korea	2361	0.25%	1	3	4	8	1.79%	1	3	8	12	0.59%
Taiwan	27	0.00%	0	2	2	4	0.89%	0	1	3	4	0.2%
South Africa	40	0.00%	4	2	2	8	1.79%	4	2	2	8	0.39%
Total	948177	1	**149**	**152**	**146**	**447**	**100.00%**	**700**	**661**	**674**	**2,035**	**100**

Table 18. Statistical description and correlation (obs=15488)

Variables	Mean	S.D	1	2	3	4	5	6	7	8	9	10	11	12
1.GPTs	.312	.463	1.000											
2.GPT_primary_Ind	.083	.276	.417	1.00										
3.ICTs	.085	.280	-.017	.007	1.00									
4.ICT_primary_Ind	.008	.087	.037	.292	.287	1.00								
5.Primary Tech	.234	.424	.031	.544	-.104	.159	1.00							
6.Prmary_Tech share	.614	.186	.126	-.157	.025	-.097	-.551	1.00						
7.Primary_tech share p1	.207	.314	.028	-.031	-.003	-.024	-.113	.250	1.00					
8.Primary_tech share p3	.209	.307	.027	-.029	.026	-.018	-.104	.170	-.449	1.00				
9. tech_ind intl p1	.215	.353	-.045	-.030	-.029	-.003	-.033	.045	.814	-.415	1.00			
10. tech_ind foreign share	.136	.103	-.087	-.091	-.092	-.057	-.094	.078	-.089	.110	-.043	1.00		
11. tech foreign share	.113	.035	-.136	-.030	-.186	-.064	.014	-.032	-.174	.160	-.149	.326	1.00	
12. prim_ind host share	.147	.230	-.031	-.057	-.013	-.008	-.074	.040	.034	-.027	.067	.043	-.025	1.00

Table 19. OLS Regression Results on the foreign share of MNC innovation activities

	The foreign share of tech56				The foreign share of tech within MNCs	The foreign share of MNC primary tech
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Constant	.0203***	.0171***	.0152***	.0163***	.138*** (.023)	.070***(.006)
Primary	-..0055***	.0008				
GPT_primary		-.0189***				
GPTs			-.0127***	-.0220***		
GPT_non-primary				.0115***		
GPT_primary_Ind					-.034*** (.011)	-.003(.006)
Tech_Ind share	-.0509***	-.0389***	-.0361***	-.0266**		
Prmary_Tech share	.0076**	.0118	.0178***	.0157***	-.089*** (.026)	
Ind foreign share	.8978***	.8976***	.9013***	.9006***	.501*** (.074)	
Tech_Ind foreign share						.341***(.040)
R-sq	.1673	.1686	.1698	.1702	.030	.344
Adjusted R-sq	.1672	.1684	.1696	.1701	.029	.332
N. of observations	2688	2688	2688	2688	2688	168

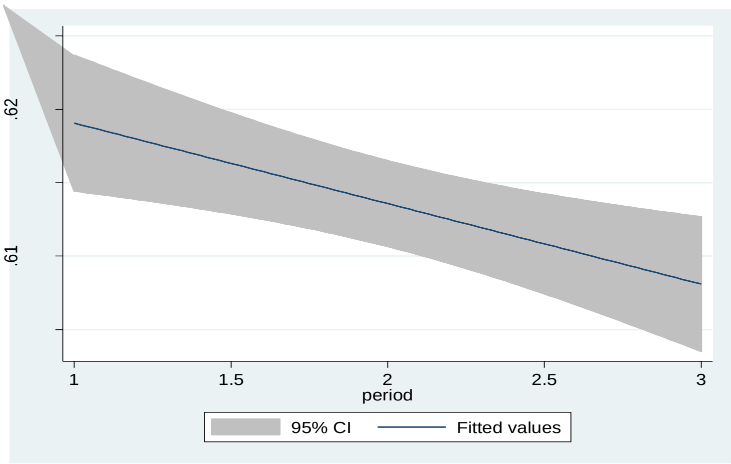
* $p < .10$
** $p < .05$
*** $p < .01$

Table 20. Regression Results on the degree of internationalization of MNC innovation activities

Variables	Model 7 Tech Intl (across MNCs)	Model 9 Tech Intl (across MNCs)
Constant	.645***(.005)	.676***(.012)
Primary		
GPTs	-.130***(.01)	
GPT*non-primary	.067***(.011)	
GPT_primary_Ind		-.049***(.006)
Foreign		
Primary_Ind share		.091***(.016)
Tech_Ind foreign share	.621***(.025)	
R-sq	.057	.014
Adjusted R-sq	.057	.014
N. of observations	15488	15488

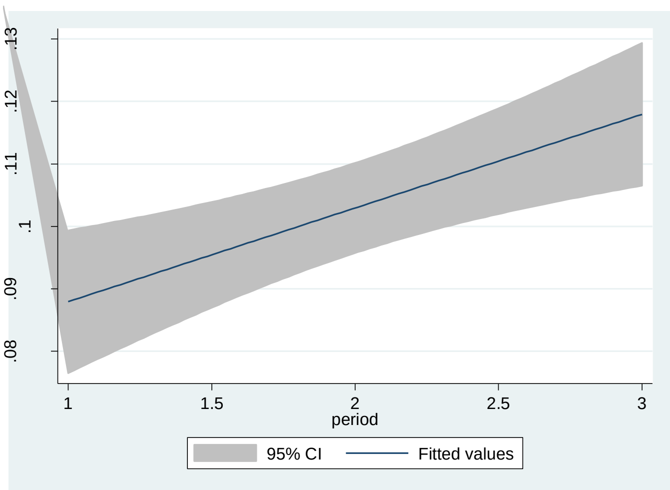
* $p < .10$
** $p < .05$
*** $p < .01$

The share of core technologies in each Industry-Countr y group

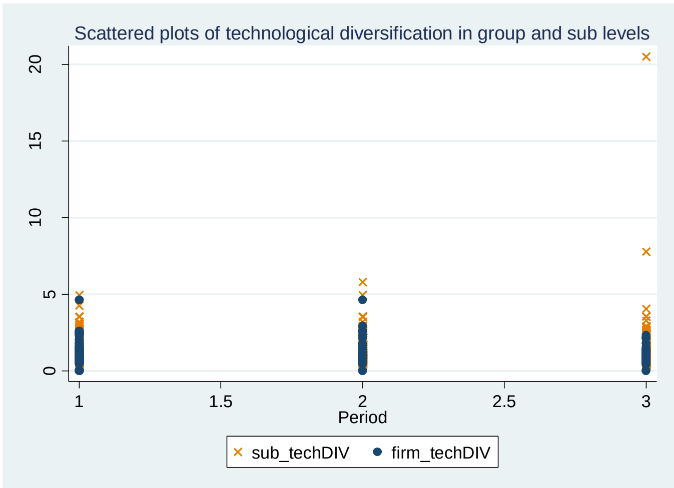


Graph 1. Fitted plots of the shares of primary technology fields that are developed across all MNC groups over time

The foreign share of core technologies in each Industry-Countr y group



Graph 2. Fitted plots of the shares of primary technology fields across all MNC groups that are developed in foreign countries over time



Graph 3. The technological diversification of MNC groups and foreign subsidiaries over time

Table 21. Statistical description and correlations (obs=2035)

Variables	Mean	S.D	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. TECH DIV	.8854	.2754	1.0000															
2. GEO DIS	1.1882	1.1305	.1138**	1.0000														
3. SUB TECH DIV	.8694	.8025	.2004**	.0399+	1.0000													
4. MNC PSHARE	.3072	.1797	-.1852	-.1617	-.0314	1.0000												
5. SUB PSHARE	.0430	.1169	-.1569**	-.2830**	.0266	.0632+	1.0000											
6. SUB_GPT_S	.5010	.2836	.0206	-.0437+	-.3408**	-.0461*	.2324**	1.0000										
7. SUB_NP_GPT_S	.5426	.3067	.0393+	-.0106	.2506**	-.1087**	.2269**	.4985**	1.0000									
8. GPT_BASED_MNC	.3484	.4766	-.0611+	-.1284**	-.0108	.5634**	.0438*	.0109	-.2261**	1.0000								
9. Foreign	.7995	.4005	-.1148**	-.2296**	.0295	.0583**	.8886**	.2009**	.2076**	.0390+	1.0000							
10. number of subs (MNC)	8.8929	5.6304	-.1700**	-.4470**	-.0248	.0296	.4212**	.0851**	.0699**	.0769**	.3522**	1.0000						
11. Firm size (patents)	.2402	.2823	-.1741**	-.2994**	-.0275	-.1375**	.2435**	.0101	-.0053	-.0280	.2047**	.6759**	1.0000					
12. Industry size (patents)	.0825	.0766	-.0750**	-.1662**	-.0346	.6184**	.0869**	.0725**	-.1102**	.6736**	.0741**	.1735**	-.1192**	1.0000				
13. Sub size (patents)	.1982	.3347	.1481**	.2799**	-.0309	-.0672**	-.9953**	-.2347**	-.2263**	-.0461*	-.8949**	-.4175**	-.2409**	-.0868**	1.0000			
14. Period1	.3440	.4752	.0146	-.0540	-.0388+	-.0455*	.0163	.0973	.0813	-.0084	.0138	.0825**	.0741**	-.0136	-.0173	1.0000		
15. Period2	.3248	.4684	.0588+	.0536*	.0363	.0026	-.0184	-.0399+	-.0245	-.0006	-.0143	-.0837**	-.0352	-.0189	.0203	-.5022**	1.0000	
16. Period3	.3312	.4708	-.0731**	.0012	.0030	.0433	.0019	-.0585**	-.0578**	.0092	.0003	.0000	-.0398+	.0325	-.0027	-.5096**	-.4881**	1.0000

+ p<0.1
* p<0.05
** p<0.01

Table 22. Fixed-effect GLS regression results at MNC group level

		Technological diversification		Geographical Dispersion	
	Model 1 TECH INTL	**Model 2 MNC TECH DIV**	**Model 3 MNC TECH DIV**	**Model 4 MNC GEO DIV**	**Model 5 MNC GEO DIV**
Constant	.6929***	.9658***	1.0330***	1.9253***	2.0441***
GPT	**-.1107*** **				
NC_GPT	**.0183*** **				
CORE	**.0095*** **				
GPT share		**-.0175**	**-.0653**	**-.0307**	**-.2902**
NC_GPT share			**.2702** **		**.7006**
Control Variables					
Firm size (number of subs)		.0008	-.0111*	-.0676***	-.0816***
Firm R&D stocks		-.1844***	-.3274***	-.2307**	-.1628
Industry R&D stocks	.0377***	-.3278***	-.4570	-1.5263***	-1.4535***
Period 2	-	.0021	.0146	.0641	.0540
Period 3	.0257***	-.0319***	-.0709	.0353	.0351
Overall R-sq	.2318	.0321	.0924	.1667	.1702
Wald Chi2		53.23 (6)	79.77 (7)		74.69 (7)
N. of observations	2688	2035	2035	2035	2035

* $p < .10$
** $p < .05$
*** $p < .01$

Table 23. GLS regression results at MNC subunit level

	Core technologies in subunits				**Technological diversification in subunits**			
	Model 6	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**
	SUB PSHARE	**SUB PSHARE**	**SUB PSHARE**	**Sub (foreign) PSHARE**	**SUB TECH DIV**	**SUB TECH DIV**	**SUB TECH DIV**	**SUB (foreign) TECH DIV**
Constant	.7404***	.7300***	.1929***	.8737***	1.3820	1.3622***	1.2703***	1.4472***
SUB GPT_S	**.0388****	**-.0096**	**.0015**	**-.0090**	**-.9911*****	**-1.0962*****	**-1.1110*****	**-.1995*****
SUB NC_GPT_S		**.0581*****	**.0235****	**.0485*****		**.1223**	**.0931***	**.1220***
Foreign			**.7159*****				**.1911*****	
Control Variables								
Firm (number of subs)	.0094***	.0089***	.0046***	.0040***	.0058	.0053	.0016	.0052
Firm size	.0552**	.0563**	.0004	-.0506***	-.1797*	-.1679*	-.1652*	-.1465
Industry size	.0407	.0534	.0092	-.0841*	-.2013	-.1198	-.1413	-.1723
Period 2	.0131**	.0127***	.0069*	.0034	.0142	.0135	.0093	.0155
Period 3	.0118**	.0124***	.0055	-.0050	-.0412	-.0404	-.0442	-.0367
US	-.1272***	-.1256***	-.1438***		-.0173	-.0149	-.0338	
Overall R-sq	.1685	.1747	.8262	.1490	.1186	.1194	.1299	.1431
Wald Chi2	150.62 (7)	160.86 (8)	4327.30 (8)	143.14 (8)	253.55 (6)	254.92 (7)	267.29 (8)	250.79 (7)
N. of observations	2035	2035	2035	1627	2035	2035	2035	1627

* $p < .10$
** $p < .05$
*** $p < .01$

Table 24. Robustness tests of study I

	Model 14 TECH INTL TECH INTL	Model 15 MNC TECH DIV PSHARE	Model 16 MNC TECH DIV PSHARE	Model 17 MNC HOST NUMBER	Model 18 MNC HOST NUMBER
Constant	.6929***	.7065***	.8067***	5.4918***	5.6182***
GPTs	**-.1107*** **				
NP_GPT	**.0183*** **				
PRIMARY	**.0095*** **				
Sub_GPT_S		**.0358*** **		**-.0464**	
NP_GPT_S		**-.1462*** **		**.1342**	
GPT_P_IND			**-.1769*** **		**-1.4828*** **
Control variables					
Firm size (number of subs)		-.0018	-.1472***		
Firm R&D stocks		.0501	.0057	11.2978***	11.4058***
Industry R&D stocks	0377***	-.9657**	-2.0416	17.1314***	22.2047***
Sub R&D stocks	.			-3.7439***	-3.7552***
Period 2	-	.0076	.2355	-.6993***	-.6961***
Period 3	.0257***	.0076	.1789	.1018	-.1022
Overall R-sq	.2318	.2738	.3052	.5790	.5880
Wald Chi2		22.41 (7)	20.65 (6)	1392.70 (7)	1444.95 (6)
N. of observations	2688	2035	2035	2035	2035

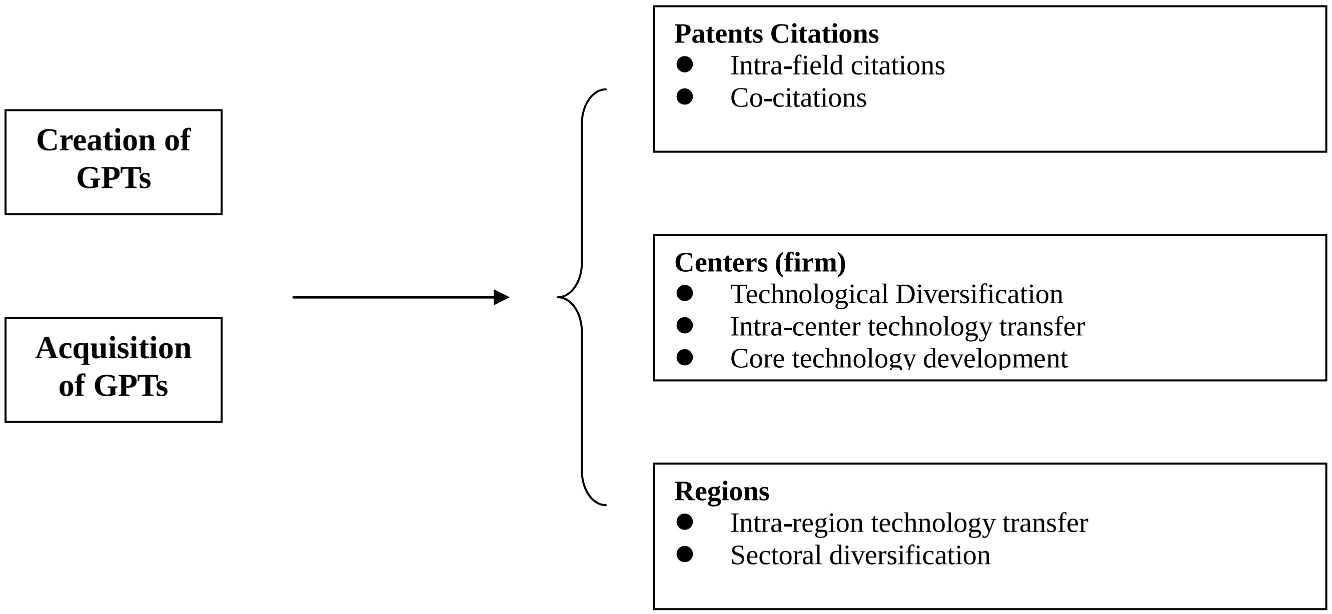


Figure 5. Empirical Model of Study III

Table 25. The description of firms, patents and patent citations by industries

	firms	Share	Firms (F-S)	Share (F-S)	Patents	Share	Citations	Share
Food, drink and tobacco	269	7.93%	56	6.76%	2112	5.55%	14050	6.32%
Chemicals	471	13.88%	152	18.36%	10398	27.34%	62911	28.28%
Pharmaceuticals	273	8.04%	53	6.40%	5106	13.42%	19246	8.65%
Metals	453	13.35%	86	10.39%	2073	5.45%	11885	5.34%
Mechanical engineering	341	10.05%	41	4.95%	1577	4.15%	8532	3.84%
Electrical equipment	448	13.20%	222	26.81%	6599	17.35%	36990	16.63%
Office equipment	87	2.56%	20	2.42%	658	1.73%	4270	1.92%
Motor vehicle	244	7.19%	61	7.37%	958	2.52%	6513	2.93%
Aircraft and transport equipment	44	1.29%	14	1.69%	73	0.2%	383	0.17%
Textile	77	2.27%	5	0.60%	156	0.41%	730	0.33%
Paper products, printing &publishing	159	4.68%	48	5.80%	820	2.16%	6781	3.05%
Rubber products	53	1.56%	8	0.97%	133	0.35%	1484	0.67%
Non-metallic mineral products	127	3.74%	11	1.33%	321	0.84%	1915	0.86%
Coal and petroleum products	175	5.16%	21	2.54%	6684	17.57%	43912	19.74%
Professional & scientific instruments	104	3.06%	28	3.38%	171	0.45%	1073	0.48%
Other manufacturing	69	2.03%	2	0.24%	200	0.53%	1753	0.79%
Total	3394	100%	828	100.00%	38039	100%	222428	100%

Table 26. The description of firms, patents and patent citations by the MNC home country

	firms	Share	Firms (F-S)	Share (F-S)	Patents U.S	Share	All Patents	Share	Citations	Share
Germany	442	13.02%	100	12.08%	7838	20.61%	90037	20.98%	47521	21.36%
UK	1028	30.29%	215	25.97%	13765	36.19%	43235	10.07%	81381	36.59%
Italy	81	2.39%	9	1.09%	416	1.09%	5230	1.22%	1873	0.84%
France	234	6.89%	61	7.37%	1686	4.43%	24949	5.81%	12305	5.53%
Japan	559	16.47%	155	18.72%	1807	4.75%	199699	46.53%	11936	5.37%
Netherlands	99	2.92%	40	4.83%	2562	6.74%	18300	4.26%	12700	5.71%
Belgium	42	1.24%	13	1.57%	242	0.64%	1383	0.32%	1432	0.64%
Switzerland	208	6.13%	49	5.92%	6029	15.85%	23307	5.43%	29806	13.40%
Sweden	272	8.01%	56	6.76%	966	2.54%	10984	2.56%	6031	2.71%
Spain	3	0.09%	0	0.00%	4	0.01%	10	0.00%	21	0.01%
Luxembourg	1	0.03%	0	0.00%	3	0.01%	309	0.07%	6	0.00%
Austria	3	0.09%	2	0.24%	3	0.01%	932	0.22%	8	0.00%
Norway	20	0.59%	8	0.97%	42	0.11%	374	0.09%	335	0.15%
Finland	47	1.38%	19	2.29%	216	0.57%	1326	0.31%	1625	0.73%
Canada	287	8.46%	85	10.27%	1380	3.63%	5304	1.24%	10405	4.68%
Australia	20	0.59%	0	0.00%	39	0.10%	327	0.08%	303	0.14%
New Zealand	10	0.29%	1	0.12%	17	0.04%	29	0.01%	173	0.08%
Panama	27	0.80%	9	1.09%	975	2.56%	1095	0.26%	4206	1.89%
South Korea	7	0.21%	4	0.48%	44	0.12%	2361	0.55%	337	0.15%
Taiwan	4	0.12%	2	0.24%	5	0.01%	27	0.01%	24	0.01%
Total	3394	100%	828	100%	38039	100%	429218	100%	222428	100%

Table 27. The distribution of citing patents across nine CBDs in the U.S

Tech	1	2	3	4	5	6	7	8	9	
1	7.46%	45.58%	33.98%	1.93%	6.08%	0.55%	0.00%	1.10%	3.31%	100%
2	2.78%	4.86%	16.67%	4.86%	6.25%	1.39%	57.64%	4.86%	0.69%	100%
3	9.72%	22.12%	12.86%	1.64%	7.17%	0.45%	33.33%	6.73%	5.98%	100%
4	0.90%	19.00%	11.76%	0.68%	9.95%	0.23%	4.30%	0.00%	53.17%	100%
5	6.32%	31.97%	24.21%	1.95%	10.98%	0.87%	12.39%	0.81%	10.50%	100%
6	9.17%	69.23%	6.07%	0.59%	2.51%	0.00%	5.03%	0.00%	7.40%	100%
7	2.42%	45.70%	25.67%	1.55%	8.05%	0.51%	10.65%	0.36%	5.09%	100%
8	0.00%	12.96%	25.93%	0.00%	23.15%	3.70%	24.07%	0.00%	10.19%	100%
9	4.28%	34.15%	19.75%	1.55%	9.84%	0.93%	25.50%	0.29%	3.70%	100%
10	11.95%	32.07%	9.04%	0.00%	41.40%	0.58%	1.75%	0.00%	3.21%	100%
11	2.62%	46.42%	15.98%	2.13%	8.69%	0.87%	11.76%	0.45%	11.08%	100%
12	2.17%	32.58%	12.80%	1.47%	8.81%	0.42%	4.08%	0.56%	37.10%	100%
13	14.44%	24.59%	22.77%	1.65%	16.75%	0.66%	4.29%	2.97%	11.88%	100%
14	5.31%	24.42%	23.14%	3.54%	18.80%	5.31%	8.12%	0.79%	10.56%	100%
15	5.88%	34.31%	21.57%	0.00%	27.45%	3.92%	0.00%	0.00%	6.86%	100%
16	5.24%	20.11%	31.55%	1.03%	11.51%	1.92%	19.24%	0.96%	8.43%	100%
17	12.85%	20.44%	31.68%	3.07%	10.80%	1.31%	7.59%	2.19%	10.07%	100%
18	6.54%	47.16%	16.40%	0.86%	13.61%	3.54%	3.00%	1.29%	7.61%	100%
19	26.56%	18.75%	3.13%	18.75%	15.63%	0.00%	0.00%	6.25%	10.94%	100%
20	7.31%	19.89%	18.40%	6.40%	19.09%	2.51%	8.57%	0.80%	17.03%	100%
21	0.00%	1.12%	39.18%	39.18%	11.19%	5.97%	1.49%	0.00%	1.87%	100%
22	48.00%	0.00%	28.00%	0.00%	0.00%	0.00%	16.00%	0.00%	8.00%	100%
23	2.61%	1.51%	4.02%	0.00%	0.80%	1.20%	85.44%	1.71%	2.71%	100%
24	0.00%	82.76%	0.00%	0.00%	0.00%	17.24%	0.00%	0.00%	0.00%	100%
25	12.50%	23.84%	2.33%	0.00%	53.49%	0.29%	2.91%	3.49%	1.16%	100%
26	15.14%	40.09%	17.48%	0.85%	4.26%	1.71%	0.85%	2.13%	17.48%	100%
27	0.00%	0.00%	5.88%	0.00%	23.53%	0.00%	0.00%	0.00%	70.59%	100%
28	12.16%	14.15%	23.81%	13.66%	15.24%	1.83%	10.41%	1.67%	7.08%	100%
29	7.33%	16.90%	35.17%	4.49%	5.85%	2.25%	13.12%	1.77%	13.12%	100%
30	17.59%	16.67%	25.93%	3.70%	0.00%	0.00%	4.63%	0.00%	31.48%	100%
31	4.67%	9.73%	52.53%	3.11%	8.95%	4.28%	6.61%	0.00%	10.12%	100%
32	3.92%	0.00%	27.45%	0.00%	54.90%	0.00%	0.00%	0.00%	13.73%	100%
33	2.29%	16.87%	13.93%	0.00%	20.90%	2.38%	18.79%	0.82%	24.01%	100%
34	6.72%	16.72%	21.19%	1.34%	4.93%	1.94%	10.60%	1.34%	35.22%	100%
35	18.63%	8.82%	10.78%	0.00%	10.78%	3.92%	0.00%	11.76%	35.29%	100%
36	2.82%	26.05%	35.15%	0.09%	2.09%	7.74%	3.83%	1.82%	20.40%	100%
37	3.65%	44.62%	36.15%	0.19%	3.46%	4.23%	1.92%	0.00%	5.58%	100%
38	6.60%	15.00%	23.09%	1.84%	17.53%	1.94%	8.19%	3.08%	22.64%	100%
39	6.00%	18.13%	25.80%	3.59%	4.08%	0.29%	12.24%	2.80%	26.54%	99%
40	2.45%	9.06%	1.70%	0.00%	1.23%	0.57%	19.06%	4.53%	61.42%	100%
41	13.62%	10.64%	10.81%	1.30%	3.72%	0.43%	14.01%	4.19%	41.29%	100%
42	1.64%	20.39%	42.43%	19.41%	3.95%	0.00%	4.93%	0.00%	7.24%	100%
43	1.03%	9.62%	32.65%	18.90%	3.44%	0.00%	0.00%	1.72%	32.65%	100%
44	2.78%	5.56%	13.89%	16.67%	22.22%	0.00%	0.00%	0.00%	38.89%	100%
45	0.66%	3.95%	2.63%	11.84%	0.00%	0.00%	48.03%	0.00%	32.89%	100%
46	0.00%	83.33%	15.63%	0.00%	0.00%	0.00%	0.00%	0.00%	1.04%	100%
47	1.55%	14.51%	50.78%	16.06%	5.70%	0.00%	0.00%	0.52%	10.88%	100%
48	2.50%	7.50%	10.00%	7.50%	0.00%	0.00%	0.00%	62.50%	10.00%	100%
49	7.03%	29.01%	21.17%	0.45%	21.71%	0.54%	12.97%	0.99%	6.13%	100%
50	4.37%	34.56%	18.27%	2.44%	19.55%	0.99%	9.61%	0.94%	9.26%	100%
51	0.33%	5.35%	29.65%	0.33%	1.23%	0.78%	58.86%	0.45%	3.01%	100%
52	8.11%	31.35%	7.03%	0.00%	0.00%	0.00%	5.95%	0.00%	47.57%	100%
53	5.63%	17.82%	24.34%	2.71%	6.59%	0.68%	8.21%	1.87%	32.15%	100%
54	0.00%	16.67%	34.62%	0.00%	20.51%	15.38%	0.00%	6.41%	6.41%	100%
55	0.00%	58.33%	4.17%	4.17%	12.50%	20.83%	0.00%	0.00%	0.00%	100%
56	3.93%	16.50%	8.63%	3.05%	4.82%	1.90%	47.84%	1.52%	11.80%	100%
Total	5.38%	27.48%	20.56%	2.48%	10.10%	1.34%	13.95%	1.38%	17.32%	100%

Table 28. The distribution of cited patents across nine CBDs in the U.S

T	1	2	3	4	5	6	7	8	9	
1	6.33%	42.88%	36.01%	1.95%	5.47%	0.12%	0.85%	0.67%	5.60%	100%
2	7.17%	13.26%	19.57%	2.61%	4.35%	1.74%	45.22%	3.26%	1.30%	100%
3	8.66%	22.47%	15.48%	1.08%	7.69%	0.48%	33.33%	5.16%	5.65%	100%
4	1.72%	20.11%	9.66%	1.49%	14.25%	0.57%	7.82%	0.11%	44.25%	100%
5	6.48%	34.45%	21.93%	1.34%	9.97%	0.83%	11.33%	1.23%	12.39%	100%
6	11.99%	66.58%	6.22%	0.38%	3.88%	0.15%	3.03%	0.08%	7.61%	100%
7	2.35%	43.52%	24.85%	1.04%	9.28%	0.40%	12.79%	0.29%	5.35%	100%
8	1.60%	15.20%	23.20%	0.80%	20.00%	5.60%	15.20%	0.00%	18.40%	100%
9	3.84%	34.00%	19.23%	1.29%	11.03%	1.22%	24.73%	0.34%	4.29%	100%
10	10.30%	32.18%	12.87%	0.26%	37.07%	1.54%	1.80%	0.39%	3.60%	100%
11	3.40%	43.02%	17.74%	1.87%	9.82%	0.86%	10.66%	0.61%	11.86%	100%
12	1.94%	30.74%	14.79%	1.53%	8.73%	0.47%	5.25%	0.47%	35.92%	100%
13	11.11%	26.08%	21.84%	3.15%	18.81%	0.88%	4.45%	3.36%	10.02%	100%
14	6.09%	25.28%	23.45%	3.65%	15.83%	5.95%	7.84%	0.98%	10.76%	100%
15	5.85%	39.89%	15.96%	2.13%	20.74%	3.19%	1.06%	0.00%	11.17%	100%
16	6.30%	22.01%	28.80%	1.68%	10.88%	1.43%	17.39%	0.68%	10.81%	100%
17	12.68%	19.42%	33.70%	3.59%	9.91%	2.11%	6.94%	1.17%	9.95%	100%
18	6.62%	42.03%	20.11%	1.40%	14.00%	3.94%	3.58%	1.80%	5.78%	100%
19	13.66%	18.63%	22.98%	13.04%	10.56%	0.00%	6.83%	3.11%	11.18%	100%
20	8.56%	16.73%	17.36%	7.47%	20.92%	2.53%	7.47%	1.24%	17.36%	100%
21	0.55%	1.29%	50.18%	25.14%	7.86%	7.30%	2.96%	0.09%	2.40%	100%
22	17.39%	5.22%	30.43%	6.96%	1.74%	0.87%	22.61%	0.87%	12.17%	100%
23	1.52%	2.36%	5.88%	0.39%	1.03%	0.65%	82.77%	1.58%	3.78%	100%
24	0.00%	73.61%	9.72%	0.00%	4.17%	6.94%	0.00%	0.00%	5.56%	100%
25	13.47%	22.10%	2.35%	0.30%	52.46%	0.98%	2.20%	4.39%	1.67%	100%
26	14.07%	37.15%	23.24%	2.06%	6.72%	0.24%	1.19%	1.34%	13.99%	100%
27	0.00%	4.92%	21.31%	1.64%	13.11%	0.00%	1.64%	0.00%	54.10%	100%
28	12.61%	15.76%	20.06%	10.21%	16.82%	1.36%	10.61%	1.52%	11.00%	100%
29	6.71%	16.39%	32.42%	5.07%	7.16%	2.80%	14.83%	1.18%	13.28%	100%
30	18.61%	19.24%	11.99%	2.52%	0.32%	0.63%	4.42%	0.00%	41.96%	100%
31	3.73%	9.77%	48.49%	5.33%	10.83%	3.20%	7.10%	0.18%	11.37%	100%
32	1.60%	10.40%	27.20%	0.00%	32.80%	0.00%	10.40%	0.00%	17.60%	100%
33	4.08%	15.01%	14.05%	0.46%	23.19%	1.56%	18.85%	0.64%	22.15%	100%
34	7.52%	14.85%	17.52%	2.72%	6.53%	1.73%	8.32%	2.08%	38.71%	100%
35	11.76%	12.32%	22.97%	0.28%	13.17%	0.84%	3.08%	10.36%	24.37%	100%
36	2.98%	25.79%	34.37%	0.58%	3.59%	7.57%	3.16%	1.55%	20.41%	100%
37	5.37%	42.28%	34.40%	0.39%	4.14%	4.98%	1.68%	0.06%	6.21%	100%
38	5.93%	13.92%	24.27%	2.18%	21.68%	1.68%	7.58%	2.62%	20.05%	100%
39	6.02%	15.13%	24.10%	6.92%	5.83%	0.29%	13.56%	2.93%	24.67%	99%
40	1.95%	10.56%	3.31%	0.10%	1.32%	0.23%	17.50%	7.64%	57.11%	100%
41	15.51%	8.12%	9.21%	1.21%	4.24%	0.41%	14.48%	5.55%	41.25%	100%
42	1.85%	23.13%	38.65%	19.65%	5.86%	0.22%	2.71%	0.33%	7.60%	100%
43	1.16%	11.38%	32.87%	16.03%	5.34%	0.93%	0.35%	2.32%	29.62%	100%
44	3.92%	15.69%	19.61%	6.86%	27.45%	0.00%	0.98%	0.98%	22.55%	100%
45	1.40%	4.21%	6.46%	9.83%	0.28%	0.00%	48.88%	0.00%	28.93%	100%
46	0.67%	66.22%	16.05%	5.35%	4.68%	1.34%	0.33%	0.00%	5.02%	100%
47	3.14%	9.12%	40.36%	15.40%	5.83%	0.90%	0.60%	1.35%	22.27%	100%
48	4.79%	19.76%	10.18%	9.58%	7.19%	0.00%	5.39%	34.73%	8.38%	100%
49	6.94%	27.47%	20.42%	1.09%	24.98%	0.68%	11.32%	0.91%	6.08%	100%
50	4.04%	33.56%	19.25%	2.08%	17.24%	2.15%	9.85%	0.81%	10.89%	100%
51	0.95%	8.99%	35.51%	0.56%	1.67%	0.78%	49.38%	0.03%	2.09%	100%
52	12.67%	28.82%	7.99%	0.00%	1.56%	0.00%	5.56%	0.35%	43.06%	100%
53	4.61%	17.49%	26.26%	3.74%	6.47%	1.13%	9.04%	1.76%	29.39%	100%
54	4.26%	17.70%	20.66%	0.98%	18.36%	24.26%	0.66%	3.93%	9.18%	100%
55	4.05%	47.30%	9.46%	4.05%	16.22%	5.41%	5.41%	0.00%	8.11%	100%
56	3.17%	22.32%	11.54%	3.79%	7.00%	2.08%	34.32%	0.87%	14.45%	100%
	5.69%	26.19%	20.96%	2.75%	10.68%	1.52%	13.68%	1.50%	16.86%	

Table 29. The comparison between the shares of citing and cited patents in each tech fields across nine CBDs

T	1	2	3	4	5	6	7	8	9
1	1.13%	2.70%	-2.03%	-0.01%	0.60%	0.43%	-0.85%	0.44%	-2.28%
2	-4.40%	-8.40%	-2.90%	2.25%	1.90%	-0.35%	12.42%	1.60%	-0.61%
3	1.06%	-0.35%	-2.63%	0.57%	-0.51%	-0.04%	0.00%	1.57%	0.33%
4	-0.82%	-1.11%	2.11%	-0.82%	-4.30%	-0.35%	-3.52%	-0.11%	8.91%
5	-0.17%	-2.48%	2.28%	0.61%	1.01%	0.05%	1.06%	-0.42%	-1.90%
6	-2.81%	2.65%	-0.16%	0.21%	-1.37%	-0.15%	1.99%	-0.08%	-0.21%
7	0.07%	2.18%	0.82%	0.51%	-1.23%	0.10%	-2.14%	0.07%	-0.26%
8	-1.60%	-2.24%	2.73%	-0.80%	3.15%	-1.90%	8.87%	0.00%	-8.21%
9	0.44%	0.15%	0.52%	0.25%	-1.19%	-0.29%	0.77%	-0.05%	-0.59%
10	1.66%	-0.11%	-3.83%	-0.26%	4.33%	-0.96%	-0.05%	-0.39%	-0.40%
11	-0.78%	3.40%	-1.77%	0.27%	-1.13%	0.00%	1.10%	-0.16%	-0.77%
12	0.23%	1.83%	-1.99%	-0.05%	0.08%	-0.04%	-1.16%	0.09%	1.18%
13	3.32%	-1.49%	0.94%	-1.50%	-2.06%	-0.22%	-0.16%	-0.39%	1.86%
14	-0.78%	-0.86%	-0.31%	-0.11%	2.98%	-0.64%	0.28%	-0.19%	-0.20%
15	0.03%	-5.58%	5.61%	-2.13%	6.71%	0.73%	-1.06%	0.00%	-4.31%
16	-1.06%	-1.90%	2.75%	-0.65%	0.63%	0.49%	1.86%	0.28%	-2.39%
17	0.17%	1.02%	-2.02%	-0.52%	0.90%	-0.79%	0.65%	1.02%	0.13%
18	-0.08%	5.13%	-3.71%	-0.55%	-0.39%	-0.41%	-0.57%	-0.52%	1.83%
19	12.90%	0.12%	-19.86%	5.71%	5.07%	0.00%	-6.83%	3.14%	-0.24%
20	-1.25%	3.16%	1.04%	-1.07%	-1.83%	-0.02%	1.10%	-0.44%	-0.33%
21	-0.55%	-0.17%	-11.01%	14.04%	3.34%	-1.33%	-1.46%	-0.09%	-0.54%
22	30.61%	-5.22%	-2.43%	-6.96%	-1.74%	-0.87%	-6.61%	-0.87%	-4.17%
23	1.09%	-0.85%	-1.87%	-0.39%	-0.23%	0.56%	2.67%	0.12%	-1.07%
24	0.00%	9.15%	-9.72%	0.00%	-4.17%	10.30%	0.00%	0.00%	-5.56%
25	-0.97%	1.73%	-0.02%	-0.30%	1.03%	-0.69%	0.71%	-0.90%	-0.50%
26	1.07%	2.93%	-5.76%	-1.20%	-2.45%	1.47%	-0.33%	0.79%	3.49%
27	0.00%	-4.92%	-15.43%	-1.64%	10.41%	0.00%	-1.64%	0.00%	16.49%
28	-0.45%	-1.60%	3.75%	3.44%	-1.58%	0.47%	-0.20%	0.15%	-3.92%
29	0.62%	0.51%	2.75%	-0.57%	-1.31%	-0.56%	-1.71%	0.60%	-0.16%
30	-1.02%	-2.58%	13.94%	1.18%	-0.32%	-0.63%	0.21%	0.00%	-10.47%
31	0.94%	-0.04%	4.04%	-2.22%	-1.89%	1.08%	-0.49%	-0.18%	-1.25%
32	2.32%	-10.40%	0.25%	0.00%	22.10%	0.00%	-10.40%	0.00%	-3.87%
33	-1.79%	1.86%	-0.12%	-0.46%	-2.29%	0.82%	-0.06%	0.19%	1.86%
34	-0.81%	1.86%	3.67%	-1.38%	-1.61%	0.21%	2.28%	-0.74%	-3.49%
35	6.86%	-3.50%	-12.18%	-0.28%	-2.38%	3.08%	-3.08%	1.40%	10.92%
36	-0.16%	0.26%	0.79%	-0.49%	-1.49%	0.17%	0.66%	0.27%	-0.01%
37	-1.72%	2.33%	1.76%	-0.20%	-0.68%	-0.75%	0.25%	-0.06%	-0.63%
38	0.67%	1.07%	-1.18%	-0.34%	-4.16%	0.26%	0.61%	0.46%	2.59%
39	-0.03%	3.00%	1.70%	-3.33%	-1.75%	0.00%	-1.32%	-0.13%	1.87%
40	0.50%	-1.50%	-1.61%	-0.10%	-0.10%	0.33%	1.55%	-3.12%	4.30%
41	-1.89%	2.51%	1.60%	0.09%	-0.52%	0.02%	-0.47%	-1.36%	0.04%
42	-0.20%	-2.73%	3.78%	-0.24%	-1.92%	-0.22%	2.22%	-0.33%	-0.36%
43	-0.13%	-1.76%	-0.22%	2.87%	-1.91%	-0.93%	-0.35%	-0.60%	3.03%
44	-1.14%	-10.13%	-5.72%	9.80%	-5.23%	0.00%	-0.98%	-0.98%	16.34%
45	-0.75%	-0.27%	-3.83%	2.01%	-0.28%	0.00%	-0.85%	0.00%	3.96%
46	-0.67%	17.11%	-0.43%	-5.35%	-4.68%	-1.34%	-0.33%	0.00%	-3.98%
47	-1.58%	5.39%	10.42%	0.67%	-0.13%	-0.90%	-0.60%	-0.83%	-11.39%
48	-2.29%	-12.26%	-0.18%	-2.08%	-7.19%	0.00%	-5.39%	27.77%	1.62%
49	0.08%	1.54%	0.76%	-0.64%	-3.27%	-0.14%	1.65%	0.09%	0.05%
50	0.34%	1.00%	-0.98%	0.36%	2.31%	-1.16%	-0.25%	0.13%	-1.63%
51	-0.61%	-3.64%	-5.86%	-0.22%	-0.44%	0.00%	9.48%	0.41%	0.92%
52	-4.57%	2.53%	-0.96%	0.00%	-1.56%	0.00%	0.39%	-0.35%	4.51%
53	1.03%	0.33%	-1.92%	-1.02%	0.12%	-0.46%	-0.83%	0.11%	2.75%
54	-4.26%	-1.04%	13.96%	-0.98%	2.15%	-8.88%	-0.66%	2.48%	-2.77%
55	-4.05%	11.04%	-5.29%	0.11%	-3.72%	15.43%	-5.41%	0.00%	-8.11%
56	0.77%	-5.83%	-2.91%	-0.74%	-2.17%	-0.18%	13.52%	0.65%	-2.65%

Table 30. Pair-wise correlation matrix of the patents and patent citations

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. INTRA-T-CIT	1.0000															
2. COCITATION	-.0104	1.0000														
3. IND-CORE	.0261	-.0135	1.0000													
4. SUB-CORE	.0296	.0137	.0339	1.0000												
5. CITED_GPT	-.0204	-.0212	-.0419	-.1860	1.0000											
6. GITED_ICT	-.0815	.0166	-.1290	-.0513	.3431	1.0000										
7. IND_SUPP_GPT	-.0227	-.0107	-.3878	-.1075	.7098	.4045	1.0000									
8. SUB_SUPP_GPT	-.0537	-.0224	-.0355	-.2904	.9477	.3131	.6700	1.0000								
9. GPT_BASED_IND	.0235	.0088	.2678	-.0997	.0689	.1776	-.2599	.0669	1.0000							
10. ICT_BASED_IND	.0321	.0066	.0636	.0962	.0579	.2101	-.0484	.0024	.1546	1.0000						
11. CHEM	-.0395	-.0099	.1422	-.1610	.0582	-.0334	-.2497	.0829	.6111	-。1006	1.0000					
12. IND	-.0017	.0328	-.1324	-.0213	.0244	-.0539	.2196	.0204	-.4935	。0680	-。5097	1.0000				
13. UK	-.0020	.0204	-.1891	-.0338	-.0139	-.0896	.1527	.0058	-.3864	-。1022	-。3047	。4010	1.0000			
14. GERMANY	-.0137	-.0096	.1150	-.0971	.0574	-.0162	-.1246	.0689	.3032	-。0774	。3532	-。3134	-。3946	1.0000		
15. SWITZERLAND	-.0146	-.0460	-.0361	-.1011	.0284	.0551	.0018	.0382	.0920	-。0617	。2877	。2925	。2899	-。2040	1.0000	
16. YEAR	-.0177	.0635	.0792	-.0399	-.0030	.0812	-.0140	.0188	.0502	。0528	。0080	。0251	-。0614	。0776	-。0379	1.0000

Table 31. Logistic Regression Results on Patent Citations of Foreign MNC Subsidiaries in the U.S

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Intra-field Citation	Intra-field Citation	Intra-field Citation	Intra-field Citation	Intra-field Citation	Intra-field Citation
Intercept	15.7493***	20.3483***	15.6383***	10.7736****	17.2342***	17.1723***
Independent Variables						
Sub Supp Tech			-.2179***	-1.6668***		
GPTs (Sub Supp Tech)				.1043***		
MNC Supp Tech					-.2007***	-.1879***
GPTs (MNC Supp Tech)						-.0248*
GPTs		-.2098***				
ICTs		.6124**				
Control Variables						
GPT-based Industry	.3152**	.2231**	.3260***	.3927***	.2671***	.2672***
ICT-based Industry	.1995**	.0597+	.2143***	.0422	.2014***	.1987***
Chemicals	-.3838**	-.2924	-.3774***	-.3450***	-.3886***	-.3935***
UK	.0010	.0146	.0218+	.1522***	.0255*	.0258*
Germany	-.0207	-.0013	.0039	.1010	-.0176	-.0171
Switzerland	.0081	-.0335*	.0310+	.1810***	.0322*	.0340*
Year	-.0077**	-.0100	-.0076***	-.0045***	-.0084***	-.0083***
No. of Observations	211842	211842	211842	211842	211842	211842
LR - Chi-Square (df)	1256.66(7)	2768.32 (9)	1830.97 (8)	10842.91 (9)	1648.81 (8)	1653.64 (9)
Pseudo R-Square	.0045	.0099	.0065	.0388	0.0059	.0059

+ p < .1
* *p* < .05
** *p* < .01
*** *p* < .001

Table 32. Logistic Regression Results on Patent Citations and Co-citations of Foreign MNC Subsidiaries in the U.S

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Sub Core	MNC Core	MNC-Sub Core	Co-citation	Co-citation	Co-citation	Co-citation
Intercept	42.2307***	-45.9535***	-91.3567***	-175.7935***	-174.9144***	-175.3353***	-177.35***
Independent Variables							
Sub Core Tech (cited)						.1887**	.2102**
MNC Core Tech (cited)							-.3176***
GPTs (supp)	-5.0133***	.3284***	.3569***				
GPTs	3.4790***	-.5739***	-.4598***		-.4402***	-.4133***	-.4104***
ICTs					.6581***	.6587***	.5328***
Control Variables							
GPT-based Industry	-.4472***	1.0357***	1.3691***	.4003***	.3268***	.3266***	.4495***
ICT-based Industry	.6388***	.0868***	-1.8898***	-.2861	-.3811*	-.4096*	-.4176*
Chemicals	-.4672***	.0199***	-.1535***	-.0749	-.0060	.0097	.0232
UK	-.8301***	-.6660***	-.4317***	.0626	.1509*	.1697**	.1389*
Germany	-.8345***	-.1880***	-.2076***	-.7101***	-.6086***	-.5965***	-.5988***
Switzerland	-1.3824***	-.6728***	.4846***	-1.0535***	-.9740***	-.9554***	-.9667***
Year	-.0213***	.0227***	.0456***	.0908***	.0905***	.0908***	.0917***
No. of Observations	211842	211842	211842	211842	211842	211842	211842
LR - Chi-Square (df)	40132.51 (9)	21111.45 (9)	30746.58 (9)	1303.96 (7)	1473.42 (9)	1480.45(10)	1523.38(11)
Pseudo R-Square	0.2055	0.0770	0.1068	.0484	.0548	.0550	.0566

+ $p < .1$
* $p < .05$
** $p < .01$
*** $p < .001$

Table 33. GLS regressions on the degree of technological diversification of each subsidiary

Variables	Model 1	Model 2	Model 3	Model 4
	Inno. DIV	**Inno. DIV**	**Tech Base DIV**	**Tech Base DIV**
Intercept	-2.8228	-2.5897	2.9947	2.5318
Independent Variables				
GPT CREATION	-.2136***	-2.0184***		.1752*
GPT CIT		-.3953***	-.6679***	-.7273***
Control Variables				
GPT-based Industry	.0637	.0709	-.0234	-.0200
ICT-based Industry	.0334	.0630	.0826	.0757
Chemicals	.0362	.0501	-.1622	-.1584
UK	.1610*	.1726***	-.0824	-.0707
Germany	.1760*	.2050**	-.2258*	-.2171+
Switzerland	.2227+	.2503**	-.1844	-.1610
Year	.0028	.0027	-.0002	-.0001
N. of observations	2654	2654	2654	2654
N. of groups	289	289	289	289
Overall R-sq	.2805	.2881	.0328	.0355
Wald Chi2	1031.24	1070.19	81.02	84.30

Table 34. Logistic regressions on the MNC and subsidiary core fields

Variables	Model 1	Model 2	Model 3
	MNC_Sub Core	**MNC_Sub Core**	**MNC_Sub Core**
Intercept	-18.9584	-6.0413	-8.4103
Independent Variables			
GPT citation (total)		.0018***	.0011
GPT citation (share)		-.1595	.0015
GPT creation (total)			.0047
GPT creation (share)			-.3573**
Control Variables			
GPT-based Industry	.7806***	.7652***	.7666***
ICT-based Industry	-.3671*	-.3076	-.3097
Other Industry	-.0293**	-.0369*	-.0343**
Chemicals	-.2275	-.3479*	-.3453*
UK	-.3378**	-.4234***	-.4382***
Germany	-.3462+	-.3118*	-.4813**
Switzerland	-.1964	-.3715+	-.4181*
Year	.0091	.0028	.0040
No. of Observations	2654	2654	2654
LR - Chi-Square (df)	103.28 (8)	124.05 (10)	128.61 (12)
Pseudo R-Square	.0313	0.0377	0.0390

Table 35. Correlation metrics in MNC subunit level (obs=8006)

Variables	Mean	S.D	1	2	3	4	5	6	7	8	9	10
1. Sub tech DIV	0.5650	1.1513	1.0000									
2. Sub tech HHI	0.8069	0.2860	-.6545	1.0000								
3. Sub share in firms	0.3848	0.3650	.0811	-.0503	1.0000							
4. Firm geo DIV	1.2124	1.0245	.1024	-.2056	-.4278	1.0000						
5. Firm geo HHI	0.5069	0.2965	-.0731	.1361	.7763	-.4792	1.0000					
6. Sub GPT share	0.4765	0.4353	.0884	-.1211	-.0582	.0239	-.0371	1.0000				
7. Sub non-primary GPT share	0.4122	0.4790	.2421	-.3395	.1053	.0902	.0766	.5696	1.0000			
8. Number of subs (firm)	5.0272	4.2032	.1687	-.2308	.6337	.0972	-.6102	.1001	-.0736	1.0000		
9. Patent stock of subs	4.2361	10.3994	.3955	-.4589	.1455	.0374	-.0002	.0556	.1599	.1552	1.0000	
10. Patent stock of firms	28.8360	39.1384	.2129	.2665	-.4803	.0295	-.2924	.0959	.0073	.7591	.3397	1.0000

Table 36. Correlation metrics in innovation division level

Variables	Mean	S.D	1	2	3	4	5	6	7	8	9
1. Sub tech DIV	0.5961	1.1747	1.0000								
2. Sub share in firms	0.3806	0.3655	.0896	1.0000							
3. CB region tech DIV	1.4547	0.3454	-.0594	-.0848	1.0000						
4. CB region ind. DIS	1.8455	.3322	-.0106	.0065	-.5500	1.0000					
5. Sub GPT share	0.5027	0.4321	.0613	-.0484	.0218	.0008	1.0000				
6. Sub non-primary GPT share	0.4348	0.4818	.2250	.1206	-.0248	.0128	.5470	1.0000			
7. Number of subs (Region)	44.6260	19.5730	.0785	.1003	-.3448	-.2789	.0260	.0538	1.0000		
8. Patent stock of subs	4.3322	10.6709	.3939	.1509	-.0891	-.0052	.0471	.1553	.0536	1.0000	
9. Patent stock of regions	220.8325	144.0876	.1040	.1142	-.4768	-.2495	.0206	.0723	.8332	.1409	1.0000

Table 37. Fixed-effect GLS Regression Results on patent creations of foreign subsidiaries in the U.S

	Subsidiaries			Multinational firms		Innovation centers	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
	Tech diversification of subs (DIV)	**Tech diversification of subs (HHI)**	**Technological importance of subs**	**Geo Dispersion of firms (DIV)**	**Geo Dispersion of firms (HHI)**	**Tech DIV of CB regions**	**IND Dispersion of CB regions**
Constant	.0480**	.9484***	.4144***	2.2508***	.3154***	1.3353***	2.0516***
Sub GPT share	**-.1692*** **	**.0693*** **	**-.0466*** **	**-.1460*** **	**.0280*** **	**-.0002**	**-.0079**
Sub non-primary GPT share	**.5305*** **	**-.2022*** **	**.0598*** **	**.3023*** **	**-.0342*** **	**.0112**	**.0230** **
Control Variables							
Sub share in firm	.2739***	-.0349***		-1.9693***	.6983***		
Number of subs (Firm)				-.0546***	-.0273***		
Number of subs (Region)						.0066***	
Patent stock of subs	.0329***	-.0094***		.0165***	-.0044***		
Patent stock of firms	.0047***	-.0013***	-.0011***	-.0045***	.0027***		
Patent stock of regions						-.0008***	-.0048***
Overall R-sq	.2061	.3097	.2408	.3005	.7112	.0266	.0783
Wald Chi2	2076.65	3588.51	43.51	185.24	1386.42	44.50	215.75
N. of observations	8006	8006	8006	8006	8006	7589	7589

* $p < .10$
** $p < .05$
*** $p < .01$

Bibliography

Almeida, P., 1996, Knowledge sourcing by foreign multinationals: patent citation analysis in the U.S semiconductor industry, Strategic Management, vol 17, 155-165;

Archibugi D., Pianta, M., 1992, The technological specialization of advanced countries, *Kluwer Academic*, Dordrecht;

Bartlett C., Ghoshal, S., 1995, Transnational management – text, cases and reading in cross-border management, IRWIN, Chicago;

Bartlett, C., Ghoshal, S., 1989, *Managing Across Borders: The Transnational Solution. Harvard Business School Press*, Boston, MA.

Bass, F., Cattin P., Wittink, D., 1978, Firm effects and industry effects in the analysis of market structure and profitability, *Journal of Marketing Research*, Vol 15, Issue 1, 3-10.

Bresnahan, T., Trajtenberg, M., 1992, General purpose technologies: “Engines of growth”, NBER Working Paper;

Bresnahan, T., Trajtenberg, M., 1995, General purpose technologies: ‘engine of growth?’, Journal of Econometrics, 83-108;

Breschi, S., Lissoni F., Malerba, F., 2003, Knowledge relatedness in firm technological diversification, *Research Policy,* Vol 32, Issue 1, 69.

Cantwell, J., 1995, The globalization of technology: what remains of the product cycle model? *Cambridge Journal of Economics*, Vol 19, 155-174;

Cantwll, J., 1992, The effects of integration on the structure of multinational corporation activity in the EC, Klein M., Welfens, P., (eds) *Multinationals in the New Europe and Global Trade*. Springer, Berlin Heidalberg, New York;

Cantwell, J., 1989. *Technological Innovation and Multinational Corporation,*. Blackwell, Oxford.

Cantwell, J., Andersen, B., 1996, A statistical analysis of corporate technological leadership historically, Economic Innovation, *New Technology,* Vol, 4, 211-234;

Cantwell, J., Fai, F., 1999, Firms as the source of innovation and growth: the evolution of technological competence. *Journal of Evolutionary Economics*, Vol 9(3),G 331-366;

Cantwell, J. and Hodson, C. (1991), Global R&D and UK Competitiveness, M. Casson (ed.), *Global Research Strategy and International Competitiveness*, Basil Blackwell, Oxford and Cambridge.

Cantwell, J., Piscitello, L, 2000, Accumulating technological competence – its changing impact on corporate diversification and internationalization. *Industrial and Corporate Change*, Vol 9(1), 21-51;

Cantwell, J., Randaccio, S., 1992, Intra-Industry Direct Investment in European. Community: Oligopolistic rivalry and technological competition, Cantwell, J., (eds) *Multinational investment in modern Europe*, Aldershot: Edward Elgar;

Cantwell, J., Santangelo, G., 2002, The new geography of corporate research in Information and Communications Technology (ICT), *Evolutionary Economics*, Vol, 12, 163-197;

Cantwell, J., Santangelo, G., 2000, Capitalism, profits and innovation in the new techno-economic paradigm, *Evolutionary Economics.* Vol, 10, 131-157;

Cantwell, J., Janne, O., 1999, Technological globalization and innovative centres: the role of corporate technological leadership and locational hierarchy, *Journal of Research Policy*, Vol, 28, 119-144;

Chari, M., Devaraj, S., David, P., 2008. The impact of information technology investments and diversification strategies on firm performance, *Management Science*, Vol 54, Issue 1, 224-234.

Chesbrough, H. and Teece, D., 1996, When is virtual virtuous? Organizing for Innovation, Harvard Business Review, Jan-Feb, 65-73;

Chung, W., Alcacer, J., 2002. Knowledge seeking and location choice of foreign direct investment in the United States, Management Science, 48, Issue 12, 1534-1554.

Cohen, W., Levinthal, D., 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly,* 35, 128-152.

Dosi, G., 1988, Sources, procedures and microeconomic effects of innovation, *Journal of Economic Literature*, 26(3), 1120-1172.

Dunning, J.; Narula, R., 1995, The R&D Activities of foreign firms in the United States. *International Studies of Management & Organization*, Vol. 25 Issue 1/2, p39-74;

Freeman, C., 1982. *The Economics of Industrial Innovation*. Pinter Publisher, London.

Freeman, C., Perez, C., 1988, Structural crisis of adjustment, business cycle and investment behaviour, Dosi, G., Freeman, C., Nelson R., Silverberg, G., Soete LLG (eds), *Technical Change and Economic Theory.* Frances Printer, London;

Frost, T., S.Birkinshaw, J.; Ensign, P., 2002, Centers of excellence in multinational CorporatioN, *Strategic Management Journal*, Vol. 23 Issue 11, p997.

Granstrand, O., 1998, Towards a theory of the technology-based firm, *Research Policy*, Vol, 27;

Grastrand, O., Patel, P., Pavitt, K., 1997, Multi-Technology corporations: why they have “distributed” rather than “distinctive core” competencies. *California Management Review*, 39, 8-25.

Grandstrand, O., Oskarsson, C., 1994. Technology diversification in multi-tech corporations, *IEEE Transactions on Engineering Management*, 41, 355-364.

Grandstrand, O., Sjolander, S., 1992. Internationalisation and diversification of multi-technology corporations, in O.Granstrand, L. Hakanson and S. Sjolander (eds), *Technology Management and International Business. Internationalisation of R&D and Technology.* Wiley: London.

Grandstrand, O., Sjolander, S., 1990, Managing innovation in multi-technology corporations, *Research Policy*, 19, 35-60.

Griliches, Z., 1990, Patent statistics as economic indicators, *Journal of Economic Literature*, XXVIII, 1661-1770;

Ghoshal, S., Bartlett, C., 1990, The multinational corporation as an interorganizational network, *Academy of Management Review*, Vol, 15,603-625;

Gupta, A., and Govindarajan, V., 2000, Knowledge flows within multinational corporations, Strategic Management Journal, Vol, 21, 473-496;

Hall, B., Trajtenberg, M., 2004, Uncovering GPTs with patent data, Working paper;

Harzing A., Noorderhaven, N., 2006, Knowledge flows in MNCs: An empirical test and extension of Gupta and Govindarajan’s typology of subsidiary roles, *International business review*, Vo 15, 195-214;

Hedlund, G., 1986. The hypermodern MNC – a heterarchy? *Human Resource Management* 25 (1), 9-35.

Helpman, E., Trajtenberg M., 1998, Diffusion of general purpose technologies, Helpman E., (eds), *General Purpose Technologies and Economic Growth.* MIT Press, Cambridge, MA.

Henderson, R., Cockburn, I., 1996, Scale, scope and spillovers: The determinants of productivity in drug discovery. *RAND Journal of Economics*, 27, Issue 1, 32-59.

Hill, C., Hoskisson, R., 1987. Strategy and structure in multiproduct firm, *Academy of Management Review,* Vol. 12, Issue 2, 331-341.

Jones, G.R., Hill, C.W. (1988), "Transaction cost analysis of strategy-structure choice", *Strategic Management Journal*, Vol. 9 No.2, pp.159-72.

Kim, D., Kogut, B., 1996, Technological platforms and diversification, *Organization Science*, Vol. 7, Issue 3, 283-301.

Kodama, F., 1992，Technology fusion and the new R&D. *Harvard Business Review,* Vol 70 (4), 70-78;

Kuemmerle, W., 1997, Building Effective R&D Capabilities Abroad, *Harvard Business Review,* Vol. 75 Issue 2;

Lei, D.; Hitt, M.; Bettis, R., 1996, Dynamic Core Competences Through Meta-Learning and Strategic Context. *Journal of Management,* Vol. 22 Issue 4, p549;

Marshall, A., 1890, *Principles of Economics.* Macmillan: London.

Murmann, P., 1998, *Knowledge and competitive advantage in the synthetic dye industry: 1850-1914,* Columbia University Business School, New York;

Nelson, R., 1992, What is 'commercial' and what is 'public' about technology, and what should be? Rosenberg N, Landdau R, Mowery DC (eds) *Technology and the Wealth of Nations*. Stanford University Press, Stanford;

Nelson R.R, Winter, S., 1982, An evolutionary theory of economic change, *Harvard University Press*, Cambridge, MA;

Nooteboom, B., 1999, Innovation, learning and industrial organization, *Cambridge Journal of Economics*, Vol 23(2), 127-150;

Oskarsson, C., 1994, Technology Analysis and Competitive Strategy: The Case of Mobile Telephones. *Technology Analysis & Strategic Management*, Vol. 6 Issue 1.

Oskarsson, C., 1993. Technology diversification – the phenomenon, its causes and effects. Doctoral Dissertation, Deparment of Industrial Management and Economics, Chalmers University of Technology, Gothenburg.

Patel, P., Pavitt, K., 1997, The technological competencies of the world's largest firms: complex and path-dependent but not much variety. *Research Policy* 26, 141-156.

Patel, P., Pavitt, K., 1991, Europe's technological performance, Freeman C., Sharp M., Walker, W., (eds) *Technology and the future of Europe: Global competition and the environment in the 1990s*. Frances Printer, London.

Patel, P., Vega, 1999, Modesto Patterns of internationalisation of corporate technology: location vs. home country advantages. *Research Policy*, Vol. 28 Issue 2/3, p145;

Pearce, R., 1999, The evolution of technology in multinational enterprises: the role of creative subsidiaries, International Business Review, Vol 8, 125-148;

Pearce, R., 1989, The Internationalization of Research and Development by Multinational Enterprises. MacMillan.

Porter, M., 1986, Competition in global industries: a conceptual framework. In

Competition in Global Industries, Porter ME (ed). Harvard Business School Press: Boston, MA; 15-60.

Prahalad, C. K.; Hamel, G., 1990, The Core Competence of the Corporation. *Harvard Business Review,* Vol. 68 Issue 3, p79-91;

Rosenberg, N., 1982, Inde the back box" Technology and economics, Cambridge: *Cambridge University Press*

Rumelt, R., 1974, Strategy, Structure and Economic Performance. *Harvard University Press:* Cambridge, MA.

Santangelo, G, 2002, The regional geography of corporate patenting in Information and Communications Technology (ICT): Domestic and foreign dimensions, *Regional studies*, Vol, 36.5, 495-514.

Santangelo, G., 1998, Corporate technological specialization in the European information and communications technology industry, *International Journal of Innovation Management, Vol 2(3)*, 339-366.

Schumpeter, J., 1934. The theory of economic development: an inquiry into profits, capital, credit, interest and business cycle, *Oxford University Press.* Oxford.

Shan, W., Song, J., 1997, Foreign direct investment and the sourcing of technology advantage: evidence from the biotechnology industry, *Journal of International Business Study*, Vol. 28, Issue 2. 267-284.

Snyder, C.R., Snyder , C.A. , and Sankar, C.S., 1998, Use of Information Technologies in the Process of Building the Boeing 777, *Journal of Information Technology Management,* IX(III): 31-42.

Teece, D., Pisano, G., Shuen, A., 1997. Firm capabilities, resources, and the concept of strategy, *Strategic Management Review* 18 (7), 509-533.

Vertova, G., 2002. A historical investigation of the geography of innovative activities, *Structural Change and Economics Dynamics*, 13, 259–283.

Wang, H., Barney, J., 2006. Employee incentives to make firm-specific investment: implications for resource-based theory of corporate diversification, *Academy of Management Review*, Vol 31, Issue 2, 466-476.

Zander, I., 1998, The evolution of technological capabilities in the multinational, *Journal of Research Policy*, Vol. 27 Issue 1.

Zander, I., 1997, Technological diversification in the multinational corporation--historical evolution and future. *Journal of Research Policy*, Vol. 26 Issue 2, 209.

Zander, U. & Kogut, B., 1995. Knowledge and the speed of the transfer and imitation of organizational capabilities: an empirical test, *Organization Science*;

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