DECLARATION FOR THE PhD THESIS
To be inserted as the first page of the thesis

The undersigned

SURNAME	Fu
FIRST NAME	Kun
PhD Registration Number	1287390

Thesis title:

Contextual Influence on Innovative Start-up Firms

PhD in	Business Administration and Management
Cycle	XXIII
Candidate's tutor	Prof. Franco Malerba; Prof. Giovanni Valentini
Year of discussion	2012

DECLARES

Under her responsibility:

1) that, according to the President's decree of 28.12.2000, No. 445, mendacious declarations, falsifying records and the use of false records are punishable under the penal code and special laws, should any of these hypotheses prove true, all benefits included in this declaration and those of the temporary embargo are automatically forfeited from the beginning;

2) that the University has the obligation, according to art. 6, par. 11, Ministerial Decree of 30th April 1999 protocol no. 224/1999, to keep copy of the thesis on deposit at the Biblioteche Nazionali Centrali di Roma e Firenze, where consultation is permitted, unless there is a temporary embargo in order to protect the rights of external bodies and industrial/commercial exploitation of the thesis;

3) that the Servizio Biblioteca Bocconi will file the thesis in its ‘Archivio istituzionale ad accesso aperto’ and will permit on-line consultation of the complete text (except in cases of a temporary embargo);

4) that in order keep the thesis on file at Biblioteca Bocconi, the University requires that the thesis be delivered by the candidate to Società NORMADEC (acting on behalf of the University) by online procedure the contents of which must be unalterable and that NORMADEC will indicate in each footnote the following information:

- thesis “Contextual Influence on Innovative Start-up Firms”;
- by Kun Fu ;
- discussed at Università Commerciale Luigi Bocconi – Milano in (year of discussion) 2012 ;
- the thesis is protected by the regulations governing copyright (law of 22 April 1941, no. 633 and successive modifications). The exception is the right of Università Commerciale Luigi Bocconi to reproduce the same for research and teaching purposes, quoting the source;

5) that the copy of the thesis deposited with NORMADEC by online procedure is identical to those handed in/sent to the Examiners and to any other copy deposited in the University offices on paper or electronic copy and, as a consequence, the University is absolved from any responsibility regarding errors, inaccuracy or omissions in the contents of the thesis;

6) that the contents and organization of the thesis is an original work carried out by the undersigned and does not in any way compromise the rights of third parties (law of 22 April 1941, no. 633 and successive integrations and modifications), including those regarding security of personal details; therefore the University is in any case absolved from any responsibility whatsoever, civil, administrative or penal and shall be exempt from any requests or claims from third parties;

7) that the PhD thesis is not the result of work included in the regulations governing industrial property, it was not produced as part of projects financed by public or private bodies with restrictions on the diffusion of the results; it is not subject to patent or protection registrations, and therefore not subject to an embargo;

Date: 31st January. 2012

Signed (write first name and surname): KUN FU

CONTEXTUAL INFLUENCE ON INNOVATIVE START-UP FIRMS

By

KUN FU

A dissertation submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

BOCCONI UNIVERSITY

Department of Management and Technology

Committee Members:

Prof. Franco Malerba (Bocconi University)

Prof. Giovanni Valentini (Bocconi University)

Prof. Stefano Breschi (Bocconi University)

January 2012

ACKNOWLEDGMENTS

Working as a PhD candidate during the past four and a half years at Bocconi University was a challenging and rewarding experience. I have had the fortune to meet and work with so many wonderful people to whom I am so grateful.

First and foremost, I wish to express great gratitude to my advisors: Prof. Franco Malerba and Prof. Giovanni Valentini for giving me such a great opportunity to work alongside them on a subject that is of great interest to me and most importantly for guiding me to grow and explore my strength and capability to be a dedicated and disciplined person. Their guidance and advice has been invaluable in shaping the core of my dissertation work as well as the final outcome. My PhD work would not have been possible if it were not for the rich and informative discussions that I have been able to engage in with them. I am very grateful and would like to express my appreciation to other member of my PhD committee: Prof. Stefano Breschi for showing his interest in my research work and for contributing his time to discuss and provide constructive comments and feedbacks on my dissertation.

I especially would like to thank to my close fellow PhD mates, great friends: Allya, Bruno, Gianluca, Martina, Masoomeh, Haoxi, Yuanji and Yulia for their support, encouragement and help for my PhD study and the final research work. Without them, my PhD life would not have been so wonderful and full of memorable moments.

I would like to acknowledge also the financial, academic and technical support of Bocconi University, especially the faulty and staff of the Department of Management and Technology and KITeS research center.

And last but not least, I would like to give my deep gratitude, appreciation and love to my great family for being all the way loving and supporting!

TABLE OF CONTENTS

TABLE OF TABLES

TABLE OF FIGURES

1. INTRODUCTION

This dissertation consists of three essays mainly attempting to examine the contextual influence on innovative start-up firms.

The first essay “***Knowledge Base of Industrial Cluster and Start-ups’ Innovation Performance***” investigates the localized knowledge spillovers in an industrial cluster and the implications for start-ups innovation performance. It explores the relationship on the one hand the characteristics of local knowledge base of the industry cluster, knowledge stock and knowledge centrality, and on the other hand innovative start-up’s technological innovation and diversification. Based on the first-hand data of over 2,000 Chinese firms located in Shanghai ICT cluster and the Chinese patent data from State Intellectual Property Office of China, I find that agglomeration externality does not benefit innovative start-ups located in a cluster equally. The attributes of firm’s entry technology in the local knowledge base play an important role in determining the way of knowledge spillovers and firm’s innovation performance.

The second essay “***Knowledge Base and Regional Technological Specialization: Evidence from ICT Clusters in China***” is an extension of the first study. This study explains why particular types of technology appear to blossom and fade in a given region over time. It takes into account inter-regional effects of the knowledge base and the moderating role of regional technology markets in different regions. The sample of this study comes from five regions in China that are concentrated with ICT industrial clusters. The findings have shown that if the knowledge centrality of a technology is high, meaning that a technology field has more connections with other technology fields in the local knowledge base, the level of specialization of the given technology (i.e. regional technology specialization or RTS) is likely to decrease due to the prevalence of localized knowledge spillovers that enhance effective circulation and communication of the knowledge from different but related technology fields and bring up opportunities worth exploring outside the focal technology field. Instead, the knowledge centrality of the technology in other regions, on average, has negligible effect on focal RTS. Local technology market, which is dedicated to promote intended technology trade and knowledge transfer barely has any influence on the former relationship, while the latter one highly depends on the development level of technology market in the other regions.

The third essay "***Intellectual Property Rights and Competition Policy on Entrepreneurship across Countries***" investigates institutions, as the rules of the game, influence the emergence and development of entrepreneurship in important ways. Specifically, it studies the impact of two economic institutions that are particularly relevant to entrepreneurship — the intellectual property rights (IPRs) and the competition policy, as well as their interaction on entrepreneurship. We propose that IPRs is positively associated with entrepreneurs adopting new technologies in the production of goods and provision of services and this effect is contingent upon the enforcement level of competition policy. The hypotheses are examined within a framework of pooling a cross-section of 60 countries during the periods between 2002 and 2007. The findings from this study show surprisingly that strengthened IPR protection adversely affects the entry of technology entrepreneurship and this relationship is attenuated by the increasing enforcement of competition policy.

2. KNOWLEDGE BASE OF INDUSTRIAL CLUSTER AND START-UPS' INNOVATION PERFORMANCE

2.1 ABSTRACT

This study explores the impact of knowledge stock and knowledge centrality, which are the two main characteristics of innovative start-ups' entry technologies in the local knowledge base, on innovative start-ups' technological innovation and diversification. It tests the hypotheses with patent and firm-level data of start-ups in Shanghai Information Communication Technology cluster from 1985 to 2009. The results show that knowledge stock and centrality of firm's entry technology in the local knowledge base has positive influence on firms' technological innovation. Over time, firms demonstrate different propensities for technological diversification in their innovation activities. Knowledge stock is negatively associated with start-ups' technological diversification. The level of knowledge stock moderates the relationship between knowledge centrality and diversification and there is a significant complementary effect between these two factors.

Keywords: Innovative start-up firm, knowledge base of industrial cluster, technological innovation and diversification

2.2 INTRODUCTION

Geographic location has been recognized as one of the key factors in explaining firm's performance, because a firm could benefit from multiple types of agglomeration externalities (Arrow, 1962; Jacobs, 1969; Marshall, 1920; Romer, 1986). Among various sources generating agglomeration externalities such as specialized suppliers, inputs at lower costs and skilled labor market from supply side and the sophisticated customer and heightened demand from demand side, localized knowledge spillover is regarded as a key ingredient of innovation and technological change (Audretsch and Feldman, 1996 and 2003; Jaffe, Trajtenberg and Henderson, 1993; Kesidou, Caniëls and Romijn, 2009). While identifying the importance of geographic agglomeration and knowledge spillover, the literature provides little insight as to how and why knowledge spills over (Audretsch and Feldman, 2003). Therefore, the way in which knowledge is most likely to spill over and the performance implication remain unclear. There are several questions still left unanswered: Why do firms within a cluster have different levels of technological innovation? Why do some firms become technologically specialized and others become diversified over time in their innovation activities within the same geographic location? How do localized knowledge spillovers influence a firm's innovation performance?

Drawing on the economic geography and innovation strategy literature, I investigate the impact of knowledge stock and knowledge centrality of innovative start-ups' entry technologies in the local knowledge base on firms' technological innovation and diversification through distinguishing the different types of technological knowledge that are agglomerated in a cluster and examining the way in which these knowledge are agglomerated (e.g. relatedness of different types of technological knowledge in the local knowledge base). ***Industry cluster*** is defined as a geographic concentration of firms operating in the same or related industries (Krugman, 1991; Porter, 1998). ***Knowledge base*** of an industrial cluster is characterized by two sets of attributes (Ramani and Looze, 2002): one attribute is ***knowledge stock*** which reflects the quantity or strength of the technological knowledge in a cluster and the other one is ***knowledge centrality*** which indicates the relatedness the focal technological knowledge with other knowledge fields. ***Innovative start-up's entry technology*** is the technology field that an innovative start-up firm chooses to start with and to build upon its business in an industrial cluster. I develop arguments， which contend that knowledge stock of an innovative start-up's entry technology in the local knowledge base has a positive effect on the firm's technological innovation but negatively influences the firm's technological diversification. Knowledge centrality positively associated with both firm's technological innovation and technological diversification. These two factors have complementary effect on the firm's technological diversification.

The sample is ***innovative start-ups*** which are newly founded firms applying their first patents shortly after their foundation in Shanghai ICT cluster from 1985 to2009. Based on China patent data and firm-level data, I test the proposed hypotheses with different specifications of negative binomial and probit model. I find that innovative start-ups have more technological innovations in the entry fields if firm's entry technology is characterized by a higher level of knowledge stock in the local knowledge base. Instead, firm produces more innovations in other related technological fields if the knowledge centrality of its entry technology is high. Over time these firms demonstrate different propensities for technological diversification in their innovation activities. Knowledge stock shows negative impact on the probability of firm's technological diversification while the influence from knowledge centrality is positive. Innovative start-ups are more likely to diversify into other related technological fields when both the knowledge stock and centrality retain a higher level.

This study offers two main contributions to the economic geography and innovation strategy literature. First, Start-up firms are known to be more prevalent in regions where industry clustering exists (Stuart and Sorenson, 2003) due to the lower costs associated with learning about the business environment for the industries of the region (Maskell, 2001). At the same time, start-up firms experience strikingly high failure rate. The way in which clusters affect start-ups' performance becomes an interesting question, yet receives limited attention. There is a large body of literature on the determinants of variation in new firm formation (e.g. Fritsch 1992; Keeble and Walker 1994; Sutaria and Hicks 2004) but very little evidence supporting that the factors fostering start-ups are the same as those, which are important for their future success (Brixy and Grotz, 2007). This study will focus on the relationship between the knowledge base of a cluster and the performance of innovative start-up and help us understand the way in which knowledge spills over among the firms within a cluster and facilitate innovative start-ups in evaluating and responding to the potential technological opportunities. Second, unlike existing studies which mainly adopt aggregated measures of the resources agglomerated in a cluster such as the location dummy which indicates whether or not a firms is located in a cluster and the size of a cluster which captures the number of firms (or innovations) in the same or related industries, I explore the local knowledge base in a way that provides information on the specificity of each type of technological knowledge (e.g. the composition and relatedness of the knowledge in a cluster) which could influence the route and potential of knowledge spillover due to the differential strength and the connections of a particular knowledge type with others. Based on the patent data, analysis carried out at the technology level provides us a deeper understanding on the mechanism of local knowledge spillover at a micro and fundamental level.

The rest of the study is structured as follows. I briefly review the background literature. Thereafter, I develop theoretical arguments leading to the hypotheses, explain the research methodology, present the results and close the study with a discussion of the findings, limitations and avenues for the future research.

2.3 THEORY AND HYPOTHESES

2.3.1 Cluster, Knowledge Spillover and Firm's Innovation Activity

There has been a long and insightful literature that considers the spatial dimension of innovative activity and the factors that influence technology change. Baptista and Swann (1998) have observed firms located in strong industrial clusters or regions are more likely to innovate than firms outside these regions and attributed the existence and success of clusters to the pervasiveness of knowledge externalities or spillovers. Jaffe et al. (1993) and Frost (2001) point out that a firm's innovation activities are influenced by the innovation activities of nearby firms, which provides strong evidence for the presence of knowledge spillovers. Beaudry and Breschi (2003) explore empirically whether firms located in strong industrial clusters are more innovative than firms located outside these regions and show that a firm is more likely to innovate if located in a region where there is strong presence of innovative firms and a large pool of potential spillovers associated with a large accumulated stock of knowledge. The theoretical foundation of these studies is mainly based on the *agglomeration/localization economies* (Marshall, 1920), which come from the clustering of firms in the same industry or the *urbanization economies* (Jacobs, 1969) that are generated from the local diversity of economic activities outside the focal industry. The problem with this stream of literature is that the driving forces behind these regional advantages are not clear. There are several sources of externalities from both the supply-side (e.g. specialized suppliers, inputs at lower costs, skilled labor market and knowledge spillover) and the demand-side (e.g. sophisticated customer and heightened demand), however, various advantages of agglomeration are usually examined as an undifferentiated phenomenon (Kesidou and Szirmai, 2008). Some scholars (e.g. Frost, 2001; Jaffe et. al., 1993) have provided evidence for the presence of localized knowledge spillovers, but they do not examine the impact on firm's innovation specifically.

Knowledge spillover refers to the effect of research performed in one economic unit in improving technology in other economic units without the latter having to pay for it (Griliches, 1992). It has received increasing attention as a key ingredient of innovation among various sources generating agglomeration externality (Audresch and Feldman, 1996, 2003; Jaffe et. al., 1993). Knowledge spillovers are typically generated by firms engaging in innovation activities and are valued as they provide knowledge that is new to the receiving firms (Gilbert, et. al., 2008). Knowledge spillovers tend to be geographically localized (Jaffe et al., 1993). Geographic location thus provides a platform upon which new economic knowledge can be produced, harnessed and commercialized into innovations (Audretsch and Feldman, 2003). Firms located in clusters have better access to information than do other firms (Bianchi and Bellini, 1991; Porter, 1990; Pouder and St. John, 1996) due to the common knowledge forming a cluster level of absorptive capacity and directly observing their rivals. With knowledge spillovers, firms are equipped with industry specific knowledge. Such knowledge of other firms' innovation activities will reduce the costs associated with the search for new knowledge and stimulate the creation of innovation (Duranton and Puga, 2001; Helsley and Strange, 2002).

Existing studies examine ‘agglomeration’ mainly from two aspects: one is the geographic scope of agglomeration which is reflected by distance-based measures such as the geographic distance (e.g. Rosenthal and Strange, 2003), zip codes (e.g. Chung & Kalnins, 2001), metropolitan statistical areas (e.g. Shaver and Flyer, 2000). The other aspect is the magnitude or strength of agglomeration which is captured by size-based measures such as the number of firms, plants, total number of employment and patents of a particular industry (e.g. Beaudry and Swann 2001; Gilbert et. al., 2008) or other related industries (e.g. Ciccone 2002; Beaudry and Breschi, 2003; Henderson 2003), revealing the ‘intra-industry’ and the ‘inter-industry’ effects respectively. The basic premise of these studies is that the agglomeration externalities increase with the size or strength of the cluster. One limit of the above mentioned studies is that they do not fully reflect the nature and specificities of the agglomerated knowledge and do not provide information on such questions as which types of knowledge are more likely to spill over and in which way they spill over. Understanding these questions is important because knowledge spillover is not only determined by the overall strength of knowledge resources but also depends on the knowledge compositions and the relatedness among them (Porter, 1998; St. John and Pouder, 2006).

2.3.2 Knowledge Stock and Knowledge Centrality

There is an increasing awareness that it is not so much the regional specialization or diversification per se that induces knowledge spillovers, innovation activities and regional growth (Bae and Koo, 2008; Boschma and Frenken, 2009) but the nature of the local knowledge such as the strength of each component of the knowledge base at the disaggregate level and the relatedness among different types of knowledge in a cluster are also considered very important. Within an industrial cluster, various kinds of knowledge that belong to different technology fields with distinctive natures are pooled together and these differences influence the relevance and the level of spillover of each type of technological knowledge.

Knowledge base is defined by Ramani and Looze (2002) as a collection of the technological knowledge that an agent (i.e. an individual, institution, a region or a nation) possesses and the connections among these knowledge. Building upon their study, I characterize the knowledge base of a geographic location by two attributes: the first one is ***knowledge stock***. It reflects the quantity of a certain type of technological knowledge within an industrial cluster. The second attribute is ***knowledge centrality*** and it indicates the relatedness the focal technological knowledge with other types of knowledge field. I use this idea as an initial building block to capture the effect of knowledge spillover from both the strength of the components (i.e. the amount of each type of technological knowledge) and their relations (i.e. the relatedness among different types of technological knowledge) in the local knowledge base.

2.3.3 Entry Technology and Absorptive Capacity

Firms do not benefit equally from the knowledge spillovers. Geographic proximity facilitates firms to access external knowledge spillovers, but it does not necessarily guarantee that the innovative start-ups absorb the knowledge spillovers and transfer them into a competitive advantage. Firms assimilate knowledge better when this knowledge is related to their technological capabilities (Audretsch and Lehmann, 2006). An important insight introduced by Cohen and Levinthal (1990) is that firms need to invest in the capacity to access and absorb external knowledge and the investment in R&D can work as a mechanism facilitating the absorption of external knowledge. The concepts of localized knowledge spillover and absorptive capacity – the ability of economic agents to recognize, assimilate and apply new scientific knowledge are thus closely linked (Agrawal, 2000).

A firm’s entry technology refers to the technological field in which a start-up firm chooses to build its business at the time of foundation. The choice of entry technology is one of the most important decisions included in the start-up’s technology strategy, which guides a firm's decisions on the development of technological capabilities and the corresponding investment (Zahra, 1996). Firm’s entry technology is captured in this study by the technological field of the first patent applied for by a start-up firm shortly after its foundation. It reflects the capabilities a firm possess to develop a certain type of technology. This is because patenting activity is technologically challenging and financially demanding. A start-up firm applying for a patent in a certain technology field soon after its foundation indicates that this firm has devoted sufficient effort and resources and gained a certain amount of capabilities in the frontier of this technology field. These initial resources and capabilities of start-ups determine their ability to access and benefit from the full potential of cluster externalities (Pe’er, Vertinsky and King, 2006). So I claim that innovative start-up firm’s entry technology represents a very important technological capability that is specific for the firms. It can be served as firm’s absorptive capacity and make the firm more capable to recognize, assimilate and apply some particular kinds of knowledge that spills over from other organizations. The above discussion has two implications: first, innovative start-ups with different entry technologies thus experience, process and response to the new knowledge from their environment differently. Second, other thing being equal, we would expect start-ups with the same entry technology at a given point in time respond to the localized knowledge spillover in a similar manner. We could also foresee that other firm level attributes such as firm size, foreign ownership and whether or not it is a stand-alone firm or affiliated to parent company could also influence the extent to which the benefit of localized knowledge spillovers accrue across these clustered firms.

2.3.4 Characteristics of Local Knowledge Base and Technological Innovation

The level of knowledge spillovers in a geographic region is influenced by the quantity of the knowledge created in this region (Acs, Braunerhjelm, Audretsch and Carlsson, 2009; Audretsch and Lehman, 2005; Beaudry and Breschi, 2003). Higher level of external knowledge indicates greater technological opportunity and higher probability of knowledge spillover (Cohen and Levinthal, 1990). In this paper, I conduct analysis at the technology level, distinguish the types of the technological knowledge and examine the strength of each knowledge type in the cluster in order to capture the different levels of spillover of various knowledge and how these differences influence firms' innovation performance. An innovative start-up firm that enters with technology characterized by a higher knowledge stock will experience more intense knowledge spillover from the entry field than might be true for innovative firms that enter with technologies characterized by lower levels of knowledge stock. This is because, firstly, the firm exposes to a larger pool of discoveries and ideas (Audretsch and Feldman, 1996; 1999) and secondly, the firm is more capable to recognize the values and assimilate this particular kind of knowledge from external environment (Cohen and Levinthal, 1990). This process will in turn facilitate the firm introduce more innovations. So I propose that:

Hypothesis 1 (H1): An innovative start-up firm will produce more technological innovations if its entry technology is characterized by a higher level of knowledge stock in the local knowledge base.

Firms do not only expose to the knowledge spillovers from their own technological field but also receive knowledge spillovers from other technological domains because the same type of technological knowledge can be applied to several other fields. This relatedness between the technologies used by firms in a cluster is thought to affect the nature and scope of knowledge spillovers (Boschma and Frenken, 2009) as they share a certain degree of heuristics and scientific principles (Breschi, Lissoni and Malerba, 2003) and knowledge is more likely to spill over between the fields when their cognitive distance is not too large to ensure effective communication and interactive learning (Nooteboom, 2000).

Based on the above argument, we could understand that the creation of new knowledge in one field depends not only on the magnitude of the investment in knowledge creation in that field per se, but also depends on knowledge spillovers from other related fields. These spillovers depend on the centrality of a certain technology field, which capture the relatedness among the different fields through which there is a circulation and spillover of knowledge (Ramani and Looze, 2002). The more the focal technological field relates to other technological fields the more knowledge spillovers it receives whenever there is new knowledge creation in any other related technological field. An innovative start-up firm that enters with technology characterized by a higher knowledge centrality in the local knowledge base will thus receive higher knowledge spillovers which will in turn facilitate the firm introduce more innovations. So I propose that:

Hypothesis 2 (H2): An innovative start-up firm will produce more technological innovations if its entry technology is characterized by a higher level of knowledge centrality in the local knowledge base.

2.3.5 Characteristics of Local Knowledge Base and Technological Diversification

Firms are likely to span over more than one technology in their innovation activities. Breschi et. al. (2003) have studied the extent and the nature of the range of firms' innovative activities and find that the knowledge-relatedness is the key factor affecting firms' technological diversification. Though they do not test the causal relationship directly, it is important to notice the fact that firms diversify technologically along certain directions, which depends on the links and the distance between technological fields. Inspired by their insightful findings, I explore in this study the determinants of innovative start-ups' technological diversification and define it as whether or not an innovative start-up firm taps into new technology fields over the observation period after its entry.

Innovation is regarded as a problem-solving process in which firms access, recombine, and manipulate knowledge to create new one (Katila and Ahuja, 2002). This process is often path-dependent and builds upon existing knowledge and routines that underpin the firm's innovation activities (Nelson and Winter, 1982). The past exploitation in a given domain makes future exploitation in the same domain even more efficient (Levinthal and March, 1993). This in turn leads to the improvement of organizational performance such as decrease of production cost (Asher, 1956), product or service quality enhancement (Argote, 1993) and organizational survival (Baum and Ingram, 1998) due to the learning effects. Although many virtues have been highlighted, organizational learning processes are also subject to some limitations such as the competence trap which drives firms to search new knowledge locally (Ahuja and Lampert, 2001; Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001) and reduces their explorative deviations from existing activities (Levinthal and March, 1993).

As firm's technological development strategy is influenced by its current environment that provides information about a distinctive opportunity to invest or strategies, which will ultimately, be associated with competitive advantage (Cockburn, Henderson and Stern, 2000). Innovative start-ups that enter with technologies characterized by high levels of knowledge stock in the local knowledge base experience intense knowledge spillover from the same technology fields and this process reinforces the accumulation of familiar knowledge which in turn facilitates firms introduce more innovations in the same technology fields. So I propose that:

Hypothesis 3 (H3): An innovative start-up firm is less likely to diversify into other technological fields if its entry technology is characterized by a higher level of knowledge stock in the local knowledge base.

There are innovative start-ups enter with technologies that can be used in many other applied areas, meaning that these technologies extensively relate with other technologies in the local knowledge base. Through well-connected knowledge network, there is a circulation and transfer of related technological knowledge (Ramani and Looze, 2002). This means that whenever there is a creation of new knowledge in the related fields there will also be a big potential of knowledge spillovers to firm's entry field. This will make the firm more open to other external technology knowledge and increase the possibility to broaden its scope of search (Argyres and Silverman, 2004; Rosenkopf and Nerkar, 2001). By responding to the potential technology opportunities, firms integrate received external knowledge with their own internal knowledge, which serves as a path-breaking mechanism and enhance the probability to explore various new technological areas eventually. So I propose that:

Hypothesis 4 (H4): An innovative start-up firm is more likely to diversify into other technological fields if its entry technology is characterized by a higher level of knowledge centrality in the local knowledge base.

There are some innovative start-ups that enter with technologies that have high levels of knowledge stock and also extensively relate with other technology fields in the local knowledge base. In this case, these firms do not only receive intensive knowledge spillovers from their entry fields, but also experience high levels of knowledge spillovers from other different but related technological fields. By doing so, firms could acquire adequate technological knowledge and develop sufficient technological capabilities in their core technological fields to the extent that these capabilities help the firms understand better and facilitate them to leverage different kinds of knowledge they receive from other technological fields. This process will eventually lead firms to explore various technological areas that are different from their entry ones. So I propose that:

Hypothesis 5 (H5): The positive (negative) effect of knowledge centrality (stock) on an innovative start-up firm's probability of technological diversification is increasing with the level of knowledge stock (centrality).

2.4 METHODS

2.4.1 Research Setting

I investigate the research questions in the context of Information Communication Technology (ICT) industry in China during the period between 1985 and 2009. ICT industry is chosen as a representative example of high-technology industries as the local knowledge plays an important role in firm's innovative activities in this industrial cluster. Theoretical and empirical studies in advanced economies underline the significance of local knowledge spillovers for innovation. However, not much is known about whether local knowledge spillovers work similarly in emerging economies (Kesidou and Szirmai, 2008), such as China. By and large, firms from these economies have been regarded as lack of sufficient capability to capture the local knowledge spillover although these countries have experienced rapid economic development over the last two decades and showed great potential to grow further and catch up even takeover the developed countries. It is interesting and also important to understand how firms from emerging economies benefit from local knowledge spillover and compare their growth patterns with the received ones from the advanced economies. China's ICT industry has experienced rapid growth sine 1990s. It is becoming the most dynamic sector in China's economy and attracting increasing attention from both the academic and business world (Meng and Li, 2002; Wang and Lin, 2008). ICT industry in China is geographically uneven at the national level. I choose one of the biggest ICT clusters in China, Shanghai cluster for this study as it is the representative one in the eastern coastal area where five out of six ICT clusters in China are located.

2.4.2 Data and Sample

It is a common method to use patent data to investigate firm and regional innovation and technological change (Co, 2002; Hicks, Breitzman, Olivastro and Hamilton, 2001; Johnson and Brown, 2004). The data used in this study is China patent applications and they are obtained from the State Intellectual Property Office (SIPO). SIPO is the governing body and directly affiliated to the State Council with main responsibilities such as organizing and coordinating IPR protection nationwide, standardizing the basic orders of patent administration, drawing up the policies of foreign-related IP work etc. This database covers 4,084,530 patents (include 1,610,798 invention, 1,373,542 utility model and 1,100,190 design) received by SIPO from 1985 (SIPO's first year of activity) to 2009 by firms, institutions and individuals of all countries seeking legal protection for their innovations. SIPO discloses the following information regarding each patent: application number, publication number, application date, publication date, priority information, international classification, applicant(s) name, applicants address, inventor(s) name, patent agency code, patent agent and abstract of the patent. Firm-level data (e.g. founding time, firm size, address/ region where the firm is located, domestic/ foreign firm, etc.) is obtained from Local Administration Office of Industry and Commerce and firm homepage from Internet.

The Organization for Economic Co-operation and Development (2009) gives the definition of ICT industry and identifies a list of International Patent Classification codes (IPC-8th edition, 2006) that are associated with ICT patents. In the current study, I use ICT-related patents with IPC code at its subclass (4-digit) level, which gives 60 technology classes across four sub-sectors of ICT industry. The IPC classification separates technical knowledge using the hierarchical levels and it can be very detailed up to 12 digits (subgroup level) and 70,000 IPC codes. The connections between different technology fields thus can be demonstrated at different level of aggregation. The problem with higher levels of aggregation (e.g. section and class-level of IPC code) is that the technologies covered by each category are too broad and heterogeneous. A higher level of aggregation in the current study means to include a lot other technology fields that are not supposed to be categories into ICT industry. On the contrary, at lower levels of aggregation (e.g. group-level of IPC code) the technical differences among technology fields become subtle and the number of patent applications concerned is likely to be too small for meaningful statistical analysis (Schmoch, 2008). IPC code at subclass (4-digit) level has been regarded as a more appropriate level of aggregation that provides clear distinction among technology fields and gives sufficient technical details of each field. It also has been frequently adopted in many studies that utilize IPC code to depict technology fields and examine patent scope (Lerner, 1994); firm's technology diversity (Laursen, Leone and Torrisi, 2010); innovation basicness (Rosell and Liu, 2011); technology generality (Hall and Trajtenberg, 2004) and regional technology portfolio (Leydesdorff, 2008).

I start with 85,394 patents in Shanghai from 1985 to 2009together with 60 technology classes of ICT industry which belong to 4 sub-sectors (Telecommunications, Consumer electronics, Computers, office machinery and Other ICT) to identify 32,783 patents of ICT industry based on IPC codes and use this data to construct the knowledge base. Based on the main IPC codes I identify 14,826 patents applied for by firms excluding the universities, research institutions and individuals to evaluate firm's innovation performance. There are 2,263 unique firms identified that patented at least once in ICT industry from 1985 to 2009. I compare the founding year of these firms with the application year of their first patent. Of the 2,263 firms, I select the firms that satisfy the following criteria.

First, the difference between the application year of firm's first patent and firm's founding year is 5 years or less. Taking 5 as the threshold value as I follow the same logic of Breschi, Malerba and Mancusi (2010) on the innovative start-ups which assumed that truly innovative new entrants are more likely to have applied for their first patent shortly after their foundation and restricted the sample to firms established not earlier than 5 years before their first patent application. Second, application year of the first patent is earlier than 2005. This is because the dependent variable (technological innovation) is measured over a time interval of 5 years. Firms applied their first patent after 2005 can't offer the complete observations for the performance measure therefore they are dropped out from the sample. To test the technological diversification model, I add in the third condition to the criteria: a firm applies for more patents apart from the first patent application after its foundation. In this sample I include only the start-ups that are active in their innovation activities because to be innovative firms in the hi-tech industry firms are supposed to be persistent in the innovation activity. In order to study the development of firm's technology trajectory, a certain level of innovation persistence is required.

Finally a sample of 207 [1] innovative start-ups are identified for technological innovation model and 131 innovative start-ups are drawn for technological

---

[1]There are in total 8 firms entering with more than one patent (i.e. multiple patents application at the same time), of which 3 firms have one technology field could be identified as dominating field that includes majority of the multiple patent applications. The rest of the firms (4 firms enter with 2 different technologies, 1 firm enters with 3 different technologies)

diversification model out of a population of 2,263 firms that have applied at least for a patent between 1985 and 2009. Additional firm-level data are collected accordingly.

2.4.3 Variables and Measures

Dependent variable. In the current study, start-up firm's innovation performance includes two aspects. One is ***technological innovation*** capturing the level of innovations introduced by an innovative start-up and it is measured by the total number of patent applications of a firm that is active in the industry and located in the cluster in the subsequent five years after its first patent application. Apart from knowing a firm's overall innovation performance I also introduce other finer measures such as ***core technological innovation*** (firm's innovation performance in its entry technology field) and ***related technological innovation*** (firm's innovation performance in all technology fields but its entry technology field) in order to capture how many of the innovations are from firm's entry technology field (i.e. core innovation) and how many are from other technology fields but related to the main field (i.e. related innovation) respectively. Based on the IPC codes of each patent, core innovation is measured by the number of patent applications with the main IPC code belongs to firms' entry technology. Related innovation is measured by the number of patent applications with one of the secondary IPC codes but not the primary one belongs to firm's entry technology. This is because according to the Guidance of Examination (SIPO, 2010), after a patent application is filed, the invention information (all novel and non-obvious technical information in the whole

---

that have equal number of patent applications in different technology fields are included in the sample as many times as the number of the identified distinguished technology fields. For example, a firm (W) has two patents filed in two different technology fields (A and B) at the same time after its entry. It will then be included in the sample twice and treated as a firm W enters with technology A and a firm W' enters with technology B in the sample.

text of a patent application such as the claims, description and drawings that represents contribution to the prior art) related to the technical subject shall be determined first, then the classifications corresponding to these information will be assigned by patent examiners. Specifically, the classification code that most adequately represents the major technical feature of invention information shall be listed first (Main classification). The technology field indicated by the main IPC code thus represents the core technology that the invention pertains to. It captures precisely the innovative nature of start-up firms and at the same time the technology field or knowledge domain to which firms have substantial contribution.

The other aspect of the innovation performance is the ***technological diversification*** of innovation activities. It is defined as whether or not an innovative start-up firm taps into a range of technology fields that are different from its entry field after entry. It is measured by a dummy variable, with 1 indicating the firm has at least one patent application in a technology field that is different from its entry field within the subsequent five years after its first patent application and 0 indicating otherwise.

Independent variables. I examine the characteristic of the technological knowledge in the local knowledge base from two aspects: knowledge stock and knowledge centrality. This concept is proposed by Ramani and Looze (2002). They define an agent (i.e. an individual, an institution, a region or a nation.) as a knowledge producer. The ***knowledge base*** of an agent is defined as a collection of the technological knowledge that an agent possesses and the connections among these knowledge fields. The knowledge base of a geographic location can be characterized by two attributes: one is ***knowledge stock*** which reflects the total amount or strength of a certain type of technological knowledge. The other attribute is ***knowledge centrality*** which indicates the relatedness the focal technological knowledge with other knowledge fields. In this study the knowledge refers to the technological knowledge. I use the terms technological knowledge, knowledge and technology interchangeably.

The total number of patent (invention) applications of ICT industry in Shanghai from 1985 to 2009 is 81,263. Every patent is attributed to one main and several, if any, supplementary technology classes by the national patent office according to International Patent Classification (IPC), which is an internationally agreed, non-overlapping and comprehensive patent classification system. Technology affiliation to one or more technological fields is assigned by SIPO to each patent in the current case and it will be indexed by j or k = 1, 2…, m. There exists a vector with m components. A component takes value 1 if the patent is affiliated to the corresponding technology and 0 otherwise. In this study, the knowledge base of Shanghai ICT cluster can thus be represented by the following matrix $\mathbf{M}_{\mathrm{i}}$:

$\mathrm{M_i} = \begin{bmatrix} \mathrm{f}_1^{\mathrm{i}} & \mathrm{c}_{12}^{\mathrm{i}} & \cdots & \mathrm{c}_{1\mathrm{m}}^{\mathrm{i}} \\ \mathrm{c}_{21}^{\mathrm{i}} & \mathrm{f}_2^{\mathrm{i}} & \cdots & \mathrm{c}_{2\mathrm{m}}^{\mathrm{i}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{c}_{\mathrm{m}1}^{\mathrm{i}} & \mathrm{c}_{\mathrm{m}2}^{\mathrm{i}} & \cdots & \mathrm{f}_{\mathrm{m}}^{\mathrm{i}} \end{bmatrix}$, in which, the technology vector of technology **k** in the knowledge base of region i (Shanghai ICT cluster in the current case) is: $\mathbf{cv}_{\mathrm{k}}^{\mathrm{i}} = (\mathrm{c}_{\mathrm{k}1}^{\mathrm{i}}, \mathrm{c}_{\mathrm{k}2}^{\mathrm{i}}, \dots, \mathrm{f}_{\mathrm{k}}^{\mathrm{i}} \dots, \mathrm{c}_{\mathrm{km}}^{\mathrm{i}})$, **k** ∈ [1, m] and $\mathrm{c}_{\mathrm{kl}}^{\mathrm{i}}$ is thenumber of patents that are affiliated both to technology k and l in region i from 1985 until a certain year t. Year t is one year before an innovative start-up firm applies for its first patent in a technology field. It is lagged one year so that I could take into count the time lag between the patent application and patent publication, which is a point in time when the patent is revealed to and accessed by the public. IPC codes in ICT industry can be split into four fields according to the International Patent Classification (8$^{\text{th}}$ edition, 2006): telecommunications, consumer electronics, computers, office machinery and other ICT. There are maximum 60 technology fields in an ICT industry cluster and m takes maximum value 60 therefore. ***Knowledge stock*** is defined as the strength or magnitude of the knowledge. The stock of technology k of region i in year t is measured by the number of patent applications (with 15% discount in number of applications per year (Hall, 2006; 2010) that are affiliated to technology k in region i until year t. From the matrix, knowledge stock of technology k in the knowledge base of region i therefore is f_k^i and it equals to the number of patents that are affiliated to technology k in region i. ***Knowledge centrality*** indicates the relatedness the focal technology with other technology fields. The centrality of technology k of region i in year t is measured by the number of technology classes with which the focal technology is co-classified[2] in the patents in region i until year t. We see from the matrix that knowledge centrality of technology k in the knowledge base of region i therefore is the number of non-zero components of technology vector $\mathbf{cv_k^i}$ = $(c_{k1}^i, c_{k2}^i, \dots, f_k^i \dots, c_{km}^i)$, other than f_k^i. For example, patent applications in region i give rise to the following 3 x 3 matrix: $M_i = \begin{bmatrix} 5 & 0 & 1 \\ 0 & 3 & 0 \\ 1 & 0 & 8 \end{bmatrix}$. According to the above definition, the knowledge stock and centrality of technology 1 (referring to the 1st row) are 5 and

[2] When a patent concerns also the constituent parts and other related subject matters of the invention that contain invention information or includes additional information which complements the invention information but does not represent contribution to the prior art and may be useful to the search, more than one classification shall be made accordingly. So the secondary classifications are assigned based on both inventive and non-inventive information. It complements the invention disclosed in the main classification and reveals other related non-trivial technical aspects in the patent document. The fact that an individual patent document is often assigned to multiple IPC codes and those codes belong to different technology fields can be interpreted as a sign of knowledge relatedness and spillovers across these knowledge domain/ technology fields that the codes refer to. Although it has been argued that the main purpose of classification is to facilitate search, the principle/guideline behind the assignment of each additional code is always based on its various relations with the core invention. Alternatively, we could also argue that patent examiners scan documents with the same code to identify other inventions with similar technical features. When a patent has been assigned several codes a broader area of search has to be covered, which indicates the technological relatedness between these technology fields (Breschi, Lissoni and Malerba, 2003).

2 respectively. The knowledge stock and centrality of technology 2 (referring to the 2^{nd} row) are 3 and 0 accordingly.

Control variables. There are firm specific and industry specific factors will affect the innovation performance of the firms. I include the following variables as controls in the model. ***Size of the firm*** has been argued to affect the firm's innovation propensity. Larger firms may have higher level of innovation activities due to the larger recourse base in terms of financial capital, human capital and organizational routines to explore new technologies. On the other hand, smaller firms have less rigid organizational structure and more flexibility adjusting their resources to conduct innovation activities. Size is introduced as control through measuring the number of employees of the firm at founding time and it is classified into small firm (0 - 100 employees), medium and large firm (more than 100 employees). I set dummy variable with the medium and large firms as the reference group. It has been argued that older firms develop more innovations due to the accumulation of experiences and capabilities over longer period of time of survival but this can also be detrimental due to organizational inertia that prevents firms from reacting to the changing environment actively. I control the ***age at entry*** of the firm as of the difference between the founding year and application year of its first patent. ***Ownership of the firm*** captures that whether a firm is invested by domestic capital, and foreign capital or both (foreign-involved). Foreign ownership is often associated with direct technology transfer from multinational companies to local affiliates, larger fraction of skilled workers and higher efficiency, thus one can expect a positive relationship between foreign ownership and innovation output. Here ownership of the firms is classified into domestic firms, foreign-involved firms. I set dummy variable with the foreign-involved firms as the reference group. ***Type of the firm*** refers to the affiliation of a firm. Firms can be classified into subsidiary firms and independent firm. I set dummy variable with the independent firms as the reference group. From the technological perspective, there are four ***sub-sectors of ICT industry*** according to IPC codes: Telecommunications, Consumer electronics, Computers, office machinery and other ICT. I set dummy variables to each sub-sector in order to capture the differential technological opportunities among these sub-sectors. ***Intensity of knowledge flow*** is to capture the magnitude of connection between each pair of technological fields, which is considered to influence the knowledge spillover between technology fields. This is because knowledge centrality only reflects the level of connections of the focal technology with other technological fields but does not take into consideration the flow of the knowledge through these connections. The knowledge flow between related technological fields could vary so greatly that alters the magnitude of the effect that is driven by the different connections among firm's entry technology and other related technological fields. It is measured by the number of patent applications that have been assigned to both technological classes in the pair. ***Team size*** is the size of the inventors' team and it is measured by the number of inventors of the first patent applied by the firm after foundation. Being listed as an inventor of a patent, a person must make original and innovative contribution to the invention. This variable thus captures the initial level of the knowledge-based human resources in an innovative start-up firm which is generally small in size and lack of human and financial recourses in initial stage. Having a larger inventors' team size indicates a firm having invested more on human capital and possessing a broader knowledge, therefore the more innovations the firm will develop. ***Co-paten*** refers to whether or not firm's first applied patent is collaborated with other applicants. I control the collaboration of the firms with other institutions (firms, universities and research institutions) as collaboration facilitates innovation through offering the firm some combination of risk sharing, obtaining access to new technologies, pooling complementary skills and speeding innovation processes (Powell, Koput and Smith-Doerr, 1996). I set dummy variables with the solo applicant as the reference group. ***Inventor experience*** refers to whether or not any inventor in the first patent of the firm has invented and applied for at least one patent before. I set dummy variables with the non-experienced inventors as the reference group. Firm's performance is likely to be affected by the competitive environment in which firm operate. Higher level of concentration implies lower level of competition, and vice versa. Innovation declines with competition, as more competition can reduce innovation incentives by lowering post-innovation profits (Gilbert, 2007). However, competition can also promote innovation by reducing the cost of failing to invest in research and development and giving firms greater incentives to pre-emptively innovate (Blundell, Griffith and Van Reenen, 1999). The ***level of concentration*** in each technological field in a certain year is controlled and measured by the Herfindahl index for patent applications in each technological field of ICT industry by the firms within the cluster.

2.4.4 Econometric Models

Technological innovation is measured by the number of patents applied for by a firm. The simplest form of a count data model is the one where the dependent variable follows a Poisson distribution, so its variance is set equal to the mean (Baptista and Swann, 1998). Since the dependent variable in the current is count data with over dispersion (variance is larger than the mean), I adopt negative binomial regression model with robust option, which is more appropriate for this analysis (Hausman and McFadden, 1984). The robust standard errors attempt to adjust for heterogeneity in the models. The other dependent variable is technological diversification and it is measured by a dummy variable that indicates whether or not a firm has at least one patent in other technological fields that is different from its entry field over the subsequent five years after its first patent application. I adopt probit regression model with robust option.

2.5 RESULTS

Descriptive statistics and correlations of the variables in the technological innovation model are presented in Table 1 and the corresponding values for technological diversification model are presented in Table 2. Table 1 shows that both knowledge stock and centrality has positive relationship with all the three alternative measures of firm's technological innovation. Table 2 shows, as expected, knowledge stock is negatively and interaction term is positively associated with technological diversification. While knowledge centrality shows unexpected negative correlation with technological diversification.

TABLE 1 DESCRIPTIVE STATISTICS AND CORRELATIONS OF VARIABLES (TECHNOLOGICAL INNOVATION MODEL)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Mean	5.31	2.30	3.00	369.75	12.15	0.67	1.98	0.75	0.49	0.31	0.09	0.33	11.33	0.42	2.52	0.12	0.30
Std. Dev.	9.82	5.85	6.04	552.70	6.84	0.47	1.55	0.43	0.50	0.47	0.28	0.47	12.03	0.49	1.79	0.32	0.28
Min	0	0	0	0.14	0	0	0	0	0	0	0	0	0.50	0	1	0	0.04
Max	65	41	45	2222.65	27	1	5	1	1	1	1	1	30.52	1	10	1	1
1 Technological innovation (total)	1.00																
2 Technological innovation (core)	0.82	1.00															
3 Technological innovation (related)	0.83	0.36	1.00														
4 Stock	0.14	0.19	0.05	1.00													
5 Centrality	0.20	0.24	0.10	0.68	1.00												
6 Size (small)	-0.25	-0.26	-0.15	-0.03	-0.06	1.00											
7 Age at entry	0.10	0.12	0.04	0.09	0.23	-0.18	1.00										
8 Ownership (domestic)	0.00	0.06	-0.07	0.06	0.05	0.15	-0.03	1.00									
9 Type (subsidiary)	-0.03	-0.08	0.04	0.06	0.04	0.35	-0.12	0.27	1.00								
10 Sector (telecommunication)	-0.02	-0.13	0.09	-0.08	-0.19	-0.06	-0.01	-0.02	-0.08	1.00							
11 Sector (customer electronics)	-0.04	0.01	-0.08	-0.28	-0.18	0.03	-0.03	-0.06	-0.03	-0.21	1.00						
12 Sector (PC, office machinery)	0.08	0.11	0.02	0.13	0.44	0.03	0.06	0.14	0.00	-0.47	-0.22	1.00					
13 Intensity of knowledge flow	0.05	0.08	0.00	0.32	0.46	-0.15	0.21	-0.11	-0.01	0.04	-0.04	-0.12	1.00				
14 Team size	0.04	0.05	0.02	0.08	0.09	0.07	0.09	-0.04	-0.01	-0.07	0.12	-0.03	0.12	1.00			
15 Co-patent	0.21	0.21	0.14	0.13	0.03	-0.18	0.14	-0.02	0.05	0.00	-0.03	-0.12	0.14	0.32	1.00		
16 Inventor experience	0.01	0.03	-0.02	0.08	0.03	-0.07	0.10	0.10	-0.02	0.02	0.00	-0.12	0.16	0.27	0.33	1.00	
17 Concentration	-0.12	-0.16	-0.03	-0.59	-0.62	-0.09	-0.10	-0.10	-0.09	0.35	0.04	-0.37	-0.29	-0.08	-0.09	-0.02	1.00

Number of observations: 207

TABLE 2 DESCRIPTIVE STATISTICS AND CORRELATIONS OF VARIABLES (TECHNOLOGICAL DIVERSIFICATION MODEL)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Mean	0.77	414.80	12.5	0.60	0.74	0.46	0.33	0.06	0.34	2.67	0.11	0.41	0.29	8.39
Std. Dev.	0.42	593.38	6.74	0.49	0.44	0.50	0.47	0.24	0.47	1.92	0.32	0.49	0.27	11.26
Min	0	0.14	0	0	0	0	0	0	0	1	0	0	0.04	1
Max	1	2222.65	27	1	1	1	1	1	1	10	1	1	1	65
1 Technology diversification	1.00													
2 Stock	-0.11	1.00												
3 Centrality	-0.07	0.63	1.00											
4 Size (small)	-0.11	-0.02	-0.12	1.00										
5 Ownership (domestic)	0.01	0.09	0.07	0.12	1.00									
6 Type (subsidiary)	-0.01	0.02	-0.03	0.37	0.30	1.00								
7 Sector (telecommunication)	-0.01	-0.12	-0.24	-0.10	-0.03	-0.02	1.00							
8 Sector (customer electronics)	-0.09	-0.22	-0.12	0.01	-0.07	-0.04	-0.18	1.00						
9 Sector (PC, office machinery)	-0.07	0.09	0.45	0.02	0.13	-0.04	-0.50	-0.18	1.00					
10 Team size	-0.05	0.16	0.04	-0.12	0.09	0.13	0.00	0.04	-0.09	1.00				
11 Co-patent	-0.03	0.09	-0.01	-0.05	0.10	0.05	0.00	0.11	-0.15	0.36	1.00			
12 Inventor experience	0.09	0.13	0.11	0.08	0.00	0.07	-0.09	0.05	-0.04	0.46	0.33	1.00		
13 Concentration	0.00	-0.63	-0.63	-0.04	-0.09	-0.01	0.38	0.07	-0.37	-0.16	-0.04	-0.14	1.00	
14 No. of technological innovation	0.44	0.11	0.15	-0.21	-0.01	-0.02	0.01	-0.04	0.07	0.20	0.06	0.05	-0.11	1.00

Number of observations: 131

2.5.1 Knowledge Base and Technological Innovation

The results of estimating technological innovation model are reported in Table 3. I introduce three models to test Hypothesis 1 and Hypothesis 2. The difference among these three models is the measure of the dependent variable. Total technological innovation (Model 1), core technological innovation (Model 2) and related technological innovation (Model 3) are adopted respectively in the models. Model 1 and 2 are significant at 0.001 level, Model 3 is significant at 0.01 level. The alpha values (alpha equals to 0) for negative binomial regression models are also significant at 0.001 level, which indicates the negative binomial regression model fits better than Poisson regression model.

Table 3 displays the estimates of the impact of knowledge stock and centrality on firm's technological innovation controlling for the characteristics of firm and industry. I use STATA command mfx to compute the correct marginal effect of each variable while holding other variables at their mean. The marginal effects of the variables are reported in Table 3.

TABLE 3 TECHNOLOGICAL INNOVATION MODELS (NEGATIVE BINOMIAL ESTIMATION)

	Model 1. Tech. Innovation (total)		Model 2. Tech. innovation (core)		Model 3. Tech. innovation (related)	
	Coefficient	Marginal	Coefficient	Marginal	Coefficient	Marginal
Knowledge Stock	-0.05	-0.20	0.38**	0.53**	-0.15	-0.37
Knowledge Centrality	0.07**	0.30*	0.04	0.05	0.07*	0.16*
Size [a] (small)	-0.74**	-3.62*	-1.13**	-1.98**	-0.66*	-1.85*
Age at entry	0.08	0.33	0.08	0.11	0.07	0.17
Ownership [a] (domestic)	-0.24	-1.06	0.18	0.24	-0.54†	-1.55
Type [a] (subsidiary)	0.21	0.91	0.01	0.02	0.43	1.06
Sector [a]	0.34	1.54	0.31	0.45	0.45	1.21
Sector [a] (customer	-0.20	-0.78	0.74	1.40	-0.72	-1.34†
Sector [a] (PC, office	-0.09	-0.36	0.52	0.80	-0.19	-0.44
Intensity of knowledge	-0.34*	-1.45*	-0.36†	-0.49	-0.29†	-0.72†
Inventor experience [a]	-0.17	-0.72	-0.03	-0.05	-0.18	-0.44
Team size	0.23**	0.99**	0.20*	0.28*	0.22*	0.53*
Co-patent [a]	-0.48	-1.69†	-0.36	-0.43	-0.40	-0.85
Concentration	-0.10	-0.41	-0.08	-0.11	-0.06	-0.16
Intercept	1.43†		-1.59		1.52	
χ^2	50.43***		73.76***		33.70**	
Log pseudolikelihood	-503.41		-328.78		-400.39	
No. of observation	207		207		207	

*** p< 0.001, ** p<0.01, * p<0.05, † p<0.1

(a) Marginal effect is for discrete change of dummy variable from 1 to 0.

(b) Marginal effect is calculated while hold the other variables at their mean.

Hypothesis 1 predicts that an innovative start-up will produce more technological innovations if its entry technology is characterized by a higher level of knowledge stock in the local knowledge base. Model 1 shows that knowledge stock has no effect (the coefficient is negative and not significant) on firm's total technological innovation. After introducing the finer measures of technological innovation, the core and related technological innovation, I test the alternate measures in Model 2 and Model 3 respectively. Model 2 shows that knowledge stock has positive and significant effect on firm's core technological innovation. The magnitude of the effect is 0.53. The economic meaning of the result can be understood as, other things being equal, if the logarithm value of the number of patent applications in a certain technological field within an industrial cluster increased by one, an innovative start-up entering with the same technology in the cluster would have 0.53 more patent application in its entry field during the subsequent five years after its entry. Model 3 shows that knowledge stock has no effect (the coefficient is negative and not significant) on the related technological innovation. The received results offer partial support for H1.

Hypothesis 2 proposes that an innovative start-up will produce more technological innovations if it entry technology is characterized by a higher level of knowledge centrality in the local knowledge base. Table 3 shows that knowledge centrality has significant and positive effects on both total and related technological innovation. The magnitude of the effect is 0.30 and 0.16 respectively. This means other things being equal, if the number of technological fields which are related to a focal technology within an industrial cluster is increased by one, the number of patent applications in all ICT technological fields of an innovative start-up entering the focal technology field would increase by 0.30 and by 0.16 in other related fields during the subsequent five years after its entry. H2 is therefore supported by the results.

2.5.2 Knowledge Base and Technological Diversification

Table 4 presents probit regression results for a dummy codification of technological diversification. Model 4 is the baseline model including only control variables. Model

5 displays the estimates of the impact of knowledge stock (H3), knowledge centrality (H4) and Model 6 shows the interaction between knowledge stock and centrality (H5) on firm's technological diversification controlling for the characteristics of firm and industry discussed above. All the models are significant at 0.001 level indicating a good fit of the selected models.

TABLE 4 TECHNOLOGICAL DIVERSIFICATION MODEL (PROBIT ESTIMATION)

	Model 4	Model 5	Model 6
Knowledge stock		-0.54**	-0.33†
Knowledge centrality		0.01	-0.04
Stock x Centrality			0.06*
Size (small)	-0.48	-0.63	-0.7†
Ownership (domestic)	0.32	0.51	0.54
Type (subsidiary)	0.32	0.4	0.3
Sector (telecommunication)	-0.63	-0.67	-0.49
Sector (customer electronics)	-0.56	-1.32†	-1.46*
Sector (computer office machinery)	-0.92*	-1.63**	-1.99**
Team size	-0.25**	-0.34**	-0.37**
Co-patent	-0.65	-0.49	-0.32
Inventor experience	0.81*	0.96**	0.96**
Concentration	0.03	-2.16*	-3.14**
No. of technological innovation	0.97***	1.08***	1.15***
Intercept	0.74	4.32**	3.97**
χ^2	46.74***	50.47***	52.00***
Log pseudolikelihood	-46.81	-41.31	-39.08
Pseudo R2	0.34	0.41	0.45
No. of observation	131	131	131

*** p< 0.001, ** p<0.01, * p<0.05, † p<0.1

Hypothesis 3 contends that an innovative start-up is less likely to diversify into other technological fields if its entry technology is characterized by a higher level of knowledge stock in the local knowledge base. The coefficient of knowledge stock in both Model 5 and Model 6shows significant negative effect on firm's technological diversification. Hypothesis 4 proposes that an innovative start-up is more likely to diversify into other technological fields if its entry technology is characterized by a higher level of knowledge centrality in the local knowledge base. The regression result in Model 5 and Model 6 shows that the effect of knowledge centrality is inclusive and not significant. Hypothesis 5 predicts that an innovative start-up is more likely to diversify into other technological fields if its entry technology is characterized by both higher knowledge stock and centrality in the local knowledge base. The coefficient of the interaction term in Model 6 shows significant positive sign as predicted.

It is important to note that the interpretations of the coefficients here, thus the effect of each variable, are not straightforward. Because in a nonlinear regression model, the interaction effect and the effects of each interacted variables depend on other independent and control variables. They are not equal to the corresponding coefficients in the regression model and they may have different signs for different values of the variables. The statistical significance of interaction effect can’t be tested with a simple t test but have to be calculated (Ai and Norton, 2003; Hoetker, 2007; Norton, Wang and Ai, 2004). I use STATA command ‘predicnl’ and ‘inteff’ (Norton et al., 2004) to compute the marginal effects of the two interacted variables, their interaction effects, z-statistics and graph the effects for each observations of the probit model.

After running predicnl command, we can see from Table 5 that the mean effect of knowledge stock is negative (-0.07). This is the average of the effects of knowledge stock calculated for each observation. It means, on average, for one unit increase in the logarithm value of knowledge stock of a particular technology in the local knowledge base, the probability of diversification of innovative start-ups entering with the same technology will decrease by 7%. The average of effects is different from the effect of average observation that is obtained via the common approach by setting the other variables at their mean (Hoetker, 2007). Train (1986) argues that the average of effects is more informative because it is unlikely that any single observation actually has the mean value of all variables. The effect of knowledge stock varies widely. Given a predicted probability of technological diversification, for most of the observations, the effects are negative, and for a few observations, the effects are positive (see Figure 1). Overall, the magnitude of the effects has a U-shaped trend across all the observations. It decreases with the probability of technological diversification and reaches its minimum for the innovative start-ups whose predicted probability of technological diversification is around 0.5, after which the magnitude of the effect starts to increase. The effects of knowledge stock are statistically significant for the firms that have a predicted probability of technological diversification from 0.4 to 0.6 at 0.05 level (see Figure 1). For the rest of the observations, the effects are not significant.

TABLE 5 AVERAGE EFFECT OF KNOWLEDGE STOCK

Variable	Observations	Mean	Std. Dev.	Min	Max
Effect of Knowledge Stock	131	-0.07	0.10	-0.37	0.20
Standard error	131	0.07	0.05	0.00	0.27
t-statistic	131	-0.83	1.04	-4.18	1.21

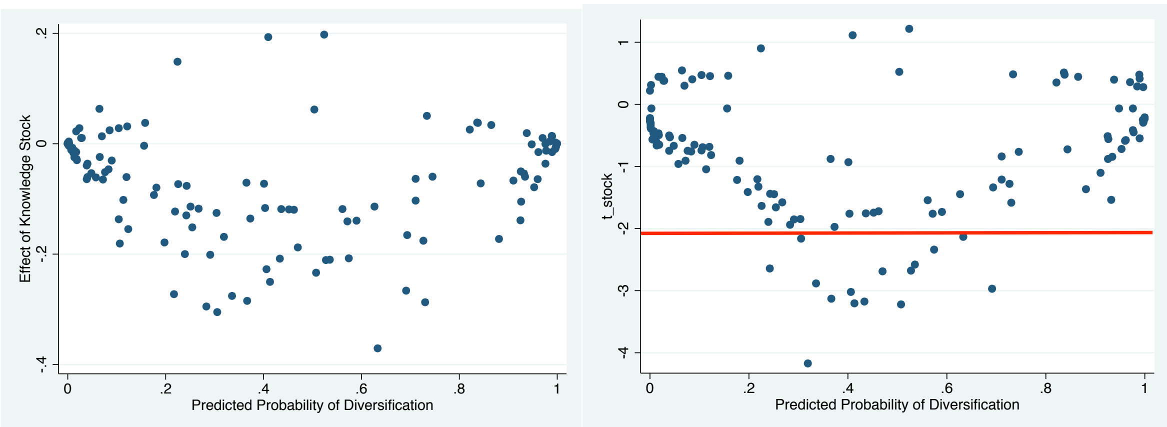

FIGURE 1 EFFECT AND STATISTICAL SIGNIFICANCE OF KNOWLEDGE STOCK ON DIVERSIFICATION

Table 6 shows that the mean effect of knowledge centrality is negative (-0.01). It means on average for one unit increase in knowledge centrality of a particular technology in the local knowledge base, the probability of technological diversification of innovative start-ups entering with the same technology will decrease by 1%. Given a predicted probability of technological diversification, for some observations, the effects are positive, and for others, the effects are negative (see Figure 2). The effects are mainly centered on zero and get largely dispersed where the innovative start-ups have the predicted probability of technological diversification around 0.5. In terms of the statistical significance of the effects, only a few observations of innovative startups whose predicted probability of technological diversification is about 0.5 have significant effect at 0.05 level. For most of the firms whose predicted probability of technological diversification is below 0.4 or above 0.6, the effects of knowledge centrality are statistically insignificant at 0.05 level.

TABLE 6 AVERAGE EFFECT OF KNOWLEDGE CENTRALITY

Variable	Observations	Mean	Std. Dev.	Min	Max
Effect of Knowledge Centrality	131	-0.01	0.02	-0.09	0.05
Standard error	131	0.01	0.01	0.00	0.08
t-statistic	131	-0.22	0.86	-2.19	1.91

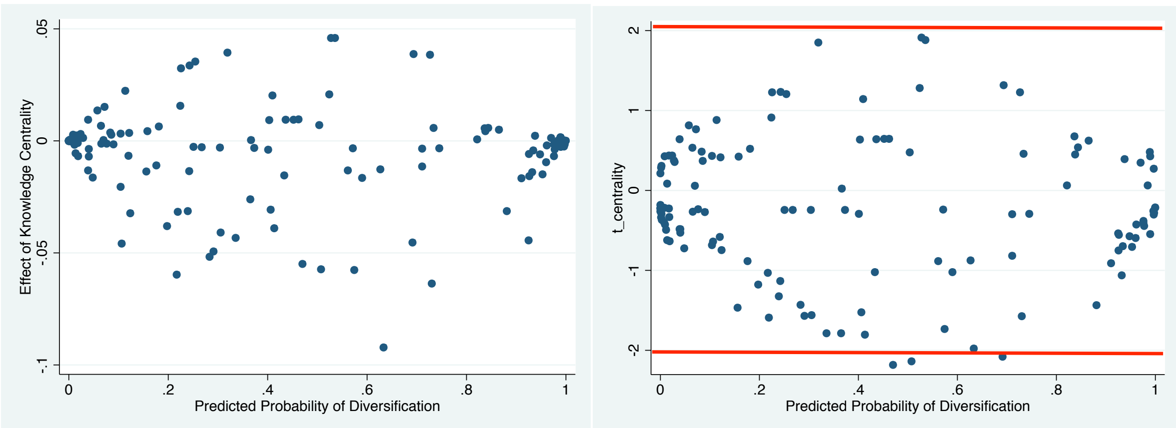

FIGURE 2 EFFECT AND STATISTICAL SIGNIFICANCE OF KNOWLEDGE CENTRALITY ON DIVERSIFICATION

After running the inteff command, we can see from Table 7 that the mean interaction effect is positive (0.01). It means on average, for one unit increase in both the logarithm value of knowledge stock and knowledge centrality of a particular technology in the local knowledge base at the same time, the probability of diversification of innovative start-ups entering with the same technology will increase by 1%. For most of the observations, the interaction effects are positive, and for a few observations that have a predicted probability of technological diversification over 0.9, the interaction effects are negative (see Figure 3). The magnitude of the interaction effect has an inverted U-shaped trend across all the observations. It increases with the predicted probability of technological diversification and reaches its maximum value (0.04) for innovative start-ups having predicted probability of technological diversification around 0.5, after which the magnitude of the interaction effect starts to decrease. In terms of the statistical significance of the interaction effects, for innovative startups whose predicted probability of diversification is around 0.4, the interaction effects are mostly significant at 0.05 level. On the other hand, for the firms that predicted probability is below 0.3 and above 0.5, only a few have statistically significant interaction effects at 0.05 level.

TABLE 7 AVERAGE EFFECT OF INTERACTION BETWEENKNOWLEDGE STOCK AND CENTRALITY

Variables	Observations	Mean	Std. Dev.	Min	Max
Interaction effect	131	0.01	0.01	-0.03	0.04
Standard error	131	0.01	0.01	0.00	0.06
z-statistic	131	0.73	1.06	-1.45	2.87

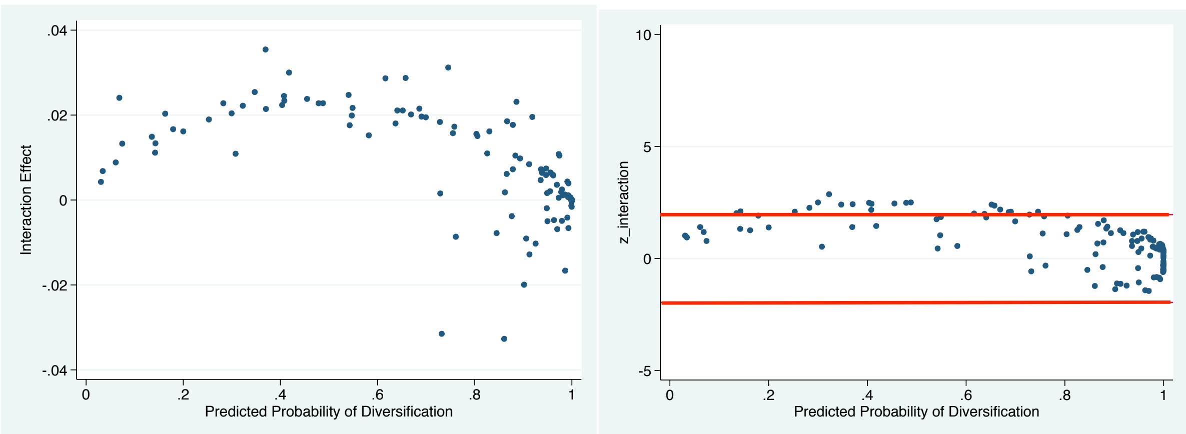

FIGURE 3 INTERACTION EFFECT AND STATISTICAL SIGNIFICANCE

2.6 DISCUSSION

2.6.1 Knowledge Base and Technological Innovation

Overall, from the results of the technological innovation model I find that higher levels of knowledge stock in an innovative start-up's entry technological field within the local knowledge base contribute only to the number of innovations that the firm produces in its entry filed (core technological innovation) and has little contribution to the technological innovation in the related technological fields (related technological innovation) and the overall technological innovation (total technological innovation) when holding other influencing factors constant.

A possible explanation for the results is two-fold. First, innovation is path-dependent and builds upon existing knowledge and routines of the firm. The past exploitation in a given domain makes future exploitation in the same domain even more efficient (Levinthal and March, 1993; Nelson and Winter, 1982). Higher knowledge stock of firm's entry technology in the cluster increases the localized knowledge spillover, which enhances the propensity and potentiality of the firm's innovation activities in its entry field. Meanwhile, higher levels of knowledge stock in a certain technological field may also setup an invisible boundary for these firms while they are looking for new solutions to the problems. This will lead firms to search locally within their entry fields and reduce the innovations in other technological fields. Because the number of total technological innovation equals to the sum of the core and related technological innovation, we observe knowledge stock only has weaker, though insignificant effect on firm's total technological innovation than its effect on the core technological innovation. Results also show that knowledge centrality has no significant influences on firm's technological innovations in the entry fields but significantly increase firm's innovation in other related fields. These results make sense by looking into different knowledge growth directions of firms, which is captured by detailed specifications of technological connections and relatedness.

Under certain circumstance, the overall growth of firm's knowledge is actually driven by the innovation that is beyond firm's core field.

2.6.2 Knowledge Base and Technological Diversification

Overall, the results obtained from the technological diversification model show that knowledge stock has predicted negative effect on innovative start-ups' technological diversification. Contrary to the prediction, knowledge centrality has on average negative effect on innovative start-ups' technological diversification. The interaction between knowledge stock and centrality has the predicted sign that indicates a positive effect. As to the statistical significance, however, all the three effects are only significant over the observations where innovative start-ups have a predicted probability of technological diversification between 0.4 and 06.

One way to interpret the pattern of the results is to argue that due to the S-shaped response curve in probit analysis, a given change in the probability is more difficult to obtain when the probability is closer to the limits of 0 and 1, and it is easier to obtain when the indeterminacy is highest, where the probability is around 0.5 (Cox and Snell, 1989; Hanushek and Jackson, 1977; Huang and Shields, 2000). We observe knowledge stock, knowledge centrality and their interaction has significant effects over the observations where innovative start-ups have a predicted probability of technological diversification from 0.4 to 06. These firms are roughly ambivalent between diversifying into other technological fields and staying in their entry fields. They are more likely to be influenced by the environmental conditions such as knowledge spillover from the outside of the firms than those firms that are more determinant to or not to diversify, thus have either much higher or lower probability to diversify. This is because the diversification decision of the latter will be more easily to achieve mainly through evaluating the firm-level resources and capabilities, while for the former, internal evaluations simply do not provide sufficient confidence to take the decision and the influences coming from their external environment become more pronounced under this situation.

Moreover, the justification of the negative effect of knowledge centrality on innovative start-ups' technological diversification could be that higher knowledge centrality implies a more fragmented market and dynamic environment. It might be a wise choice for these start-ups to stay specialized and efficient in their entry fields which is more likely to result in successful outcomes in a dynamic environment (Levitt and March, 1988) because the specialization based on core competences is difficult to imitate and can provide the basis for a sustainable competitive advantage (Barney, 1991).

2.7 CONCLUSIONS AND IMPLICATIONS

In this study, I investigated the localized knowledge spillover in an industrial cluster and the implications for start-ups innovation performance through exploring the relationship on the one hand two characteristics of local knowledge base of the industry cluster, knowledge stock and knowledge centrality, and on the other hand innovative start-up's technological innovation and diversification.

I argued that agglomeration externality did not benefit innovative start-ups in a cluster equally. Alongside the agglomeration effect, the attributes of firm's entry technology in the local knowledge base played an important role in determining the way of knowledge spillover and firm's innovation performance. Focusing on a setting where intensive knowledge spillover is likely to be observed, one of the biggest ICT clusters in China was selected. I asked first, why do firms within a cluster have different levels of technological innovation? Second, why do some firms become technologically specialized and others diversified over time although they all started with one or a few types of technologies within the same geographic location? Third, how do localized knowledge spillovers influence firm's innovation performance? The results showed that an innovative start-up produced more technological innovations if the firm's entry technology was characterized by a higher level of knowledge centrality in the local knowledge base. The knowledge stock showed only significant effect on firm's core technological innovation, which might be due to the coexistence of ‘learning’ and ‘lock-in’ effects of the firm’s innovation. This study also showed that over time innovative start-ups demonstrated different propensities of technological diversification in their innovation activities. Knowledge stock and centrality of firm’s entry technology in the local knowledge base showed on average negative effect on the probability of technological diversification. The interaction between knowledge stock and centrality showed positive effects on the probability of firm’s technology diversification. Innovative start-ups were more likely to diversify into other technological fields when both the knowledge stock and centrality retains a higher level.

This study contributes to the economic geography and innovation strategy literature by focusing on the performance implication of clustering effect on the innovative start-ups and highlighting the importance of investigating the specificities and the characteristics of the knowledge in the local knowledge base in order to understand the micro-foundations of knowledge spills over and the ways in which knowledge spillover influence firm’s innovation performance. This study also provides important practical and managerial implications. To understand the driving forces behind the superior performance of innovative start-ups located in a cluster we have to distinguish what resources have been agglomerated in the cluster, in which way they are agglomerated and which types of firms could benefit most from this agglomeration. The agglomerated resources do not benefit firms in a cluster equally. Innovative start-ups with a certain type of entry technology demonstrate better innovation performance than other firms in the same cluster. Even though entering a high-tech industry cluster, innovative start-ups should carefully choose the entry technologies upon which to build their business through evaluating the characteristics of local knowledge base in order to access, absorb and fully utilize the localized knowledge spillover.

This study has some limitations that suggest a number of directions for future research. First, generalizability of the findings from this study might be questioned in that it investigates only one cluster in one industry. This study can be extended to other hi-tech industries where the localized knowledge spillover and externality play more important role than other types of agglomeration resources. Future research could consider multi-cluster and multi-industry studies. It is interesting to ask if there are industry-specific and location-specific factors that might be relevant; if there exist a generic pattern of the relationship within an industry across different clusters or across different industries.

Second, I focus on the firm-level innovation performance. Due to the interplay between the firm and cluster, the level of analysis can be extended to the cluster or regional level. Future research can carry out studies on the cluster evolution and regional diversification in terms of technological knowledge and economic activities. The characteristics of the technological knowledge in the local knowledge base shape the development opportunities of technologies at the regional level.

Third, this study is based on China patent data that currently does not provide the information on patent citations. Patent co-classification provides sufficient information on the connections between various technological knowledge, but not sufficient to trace the real knowledge flow. Thus, I do not directly test the relationship between the knowledge spillover and firm performance. Extending the current study based on the US and European data are recommended for future studies.

Forth, the innovation performance measure in this study is based on firm's patent application. There are well-documented limitations associated with the adoption of patent data to measure the innovation output in existing literature. The current study focuses on the performance of the innovative start-up firms. The specialties of this kind of firm (it has to be new and conduct innovations), the average time (12 - 32 months) it takes from the date of application to that of the grant of a patent in China and even longer lead time to realize the commercialization of the patented invention make the patent application the most appropriate measure for firm's innovation performance since it is close to the first moment when firms make innovative achievements.

2.8 REFERENCES

Ai, C. and Norton, E.C. 2003. Interaction terms in logit and probit models. Economics Letters, 80(1): 123−129.

Acs, Z., Braunerhjelm, P., Audretsch, D.B. and Carlsson, B.2009. The knowledge spillover theory of entrepreneurship. Small Business Economics, 32(1): 15-30.

Ahuja, G. and Lampert, C.M. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal, 22 (6/7): 521-543

Almeida, P. 1996. Knowledge sourcing by foreign multinationals: patent citations analysis in the U.S. semiconductor industry. Strategic Management Journal, 17: 155–165.

Argote, L. 1993. Group and organizational learning curves: Individual, system and environmental components. *British Journal of Social Psychology*, 32: 31-51.

Argyres, N. S. and Silverman, B. S. 2004. R&D, Organization structure, and the development of corporate technological knowledge. *Strategic Management Journal*, 25: 929-958

Asher, H. 1956. *Cost-quantity relationships in the airframe industry.* Santa Monica, CA: RAND.

Audretsch, D. B and Feldman M. P. 1996. R&D Spillovers and the Geography of Innovation and Production, *The American Economic Review*, 86 (3): 630-640.

Audretsch, D.B. and Lehmann, E. E. 2005. Does the Knowledge Spillover Theory of Entrepreneurship hold for regions? *Research Policy,* 34: 1191-1202.

Audretsch, D. B and Feldman, M. P. 2003. Knowledge Spillovers and the Geography of Innovation, in J. Vernon Henderson and Jacque Thisse (Eds), *Handbook of Urban and Regional Economics*, Volume 4. Amsterdam: North Holland Publishing.

Audretsch, D.B. and Lehmann M. P. 2006. Entrepreneurial access and absorption of knowledge spillovers: Strategic board and managerial composition for competitive advantage. *Journal of Small Business Management,* 44(2): 155–166.

Bae J. and Koo J. 2008. The nature of local knowledge and new firm formation. *Industrial and Corporate Change*, 18(3): 473–496

Baptista, R. and Swann, P. 1998. Do firms in clusters innovate more? *Research Policy,* 27: 525–40.

Barney, J. 1991. Firm resources and the theory of competitive advantage. *Journal of Management*, 17: 99-120.

Baum, J. A. C., and Ingram, P. 1998. Survival-enhancing learning in the Manhattan hotel industry, 1898-1980. *Management Science*, 44 (7): 996-1016.

Beaudry, C. and Swann, P. 2001. *Growth in industrial clusters: A bird's eye view of the United Kingdom.* Stanford Institute for Economic Policy Research Discussion Paper No. 00-38, Stanford, CA: Stanford University

Beaudry C. and Breschi S. 2003. Are firms in clusters really more innovative? *Economics of Innovation and New Technology*, 12(4): 325–342.

Bianchi, P. And Bellini, N. 1991. Public policies for local networks of innovators. *Research Policy,* 20: 487-497.

Blundell, R and Griffith, R. and Van Reenen, John. 1999. Market share, market value and innovation in a panel of British manufacturing firms. *Review of economic studies*, 66(3): 529-554.

Boschma, R. A. and Frenken, K. 2009. Some notes on institutions in evolutionary economic geography. *Economic Geography*, 85 (2): 151-158.

Breschi, S. Malerba, F. and Mancusi, M. L. 2010. Survival of innovative entrants in knowledge intensive sectors. In F. Malerba (Eds.), *Knowledge Intensive Entrepreneurship and Innovation Systems: Evidence From Europe*. Chapter 12. London and New York: Routledge.

Breschi, S., Lissoni, F., Malerba, F. 2003. Knowledge-relatedness in firm technological diversification. *Research Policy,* 32: 69–87.

Brixy and Grotz, 2007. Regional patterns and determinants of birth and survival of new firms in Western Germany. *Entrepreneurship & Regional Development*, 19: 293–312.

Co, C. 2002. Evolution of the geography of innovation: evidence from patent data. *Growth and Change,* 33: 393–423.

Cockburn, I.M., Henderson, R.M. and Stern, S. 2000. Untangling the origins of competitive advantage. *Strategic Management Journal*, 21: 1123-1145.

Cox, D. R., and Snell, E. J. 1989. *Analysis of binary data* (2nd ed.). London: Chapman and Hall.

Deeds, D.L., Decarolis, D., Coombs, J.E. 1997. The impact of firm-specific capabilities on the amount of capital raised in an initial public offering: evidence from the biotechnology industry. *Journal of Business Venturing,* 12: 31–46.

Duranton, G. and Puga, D. 2001. Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review*, 91 (5): 1454-1477.

Fritsch, M. 1992. Regional differences in new firm formation: evidence from West Germany, *Regional Studies*, 25: 233–241.

Frost, T.S. 2001. The geographic sources of foreign subsidiaries' innovations. *Strategic Management Journal,*22: 101–123.

Gilbert, B. A., McDougall, P. P. and Audretsch, D. B. 2008. Clusters, knowledge spillovers and new venture performance: An empirical examination. *Journal of Business Venturing*, 23: 405–422.

Gilbert, R. J. 2007.*Competition and Innovation*. Competition Policy Center, Institute for Business and Economic Research, UC Berkeley.

Griliches, Z. 1992. The Search for R&D Spillovers. *Scandinavian Journal of Economics*, 94(supplement): S29-S47.

Hall, B. and Trajtenberg, M., (2004). Uncovering GPTs with patent data. NBER WORKING PAPER SERIES Working Paper 10901.

Hanushek, E. A., and Jackson, J. E. 1977. *Statistical methods for social scientists*. New York: Academic Press. pp. 183-184.

Hausman J, McFadden D. 1984. Specification tests for the multinomial logit model. *Econometrica,*52(5): 1219–1240.

Helsley, R. W. and Strange, W. C. 2002. Innovation and input sharing. *Journal of Urban Economics,* 51 (1): p25-45.

Henderson, R. and Cockburn I. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal,* 15: 63-84.

Hicks, D., Breitzman, T., Olivastro, D., Hamilton, K.2001. The changing composition of innovative activity in the US – a portrait based on patent analysis. *Research Policy*, 30: 681–703.

Hoetker, G. 2007. The use of logit and probit models in strategic management research. *Strategic Management Journal*, 28: 331-343.

Huang, C. and Todd S. T. 2000. Interpretation of interaction effects in logit and probit analyses: Reconsidering the relationship between registration laws, education, and voting turnout. *American Politics Quarterly*, 28(1): 80-95.

Jacobs, J. 1969. *The economy of cities*. NY, USA: Random House.

Jaffe, A.B., Trajtenberg, M., Henderson, R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*,63: 577–598.

Johnson, D. K. N. and Brown, A. 2004. How the West has won; regional and industrial inversion in U.S. patent activity. *Economic Geography*, 80: 241–260.

Katila, R.; Ahuja, G.2002. Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, 45 (6): 1183-1194.

Keeble, D. and Walker, S. 1994. New firms and dead firms: spatial patterns and determinants in the United Kingdom. *Regional Studies*, 28: 411–427.

Kesidou, E. and Szirmai, A. 2008.Local knowledge spillovers, innovation and export performance in developing countries. Empirical evidence from the Uruguay software cluster. *European Journal of Development Research*, 20(2): 281-298.

Kesidou, E., Caniëls, M.C.J., Romijn, H.A. 2009. Local knowledge spillovers and development: an exploration of the software cluster in Uruguay. *Industry and Innovation*, 16(2): 247-272.

Krugman P. 1991. *Geography and Trade*. Cambridge, MA: MIT Press.

Lerner, J., (1994). The importance of patent scope: an empirical analysis. The RAND Journal of Economics. 25, 319-333.

Leydesdorff, L., (2008). Patent Classifications as Indicators of Intellectual Organization. Journal of the American Society for Information Science & Technology 59(10): 1582–1597

Maskell, P. 2001. Towards a knowledge-based theory of the geographical cluster. *Industrial and Corporate Change,* 10 (4): 921–943.

Meng, Q.X. and Li, M.Z. 2002. New economy and ICT development in china. *Information Economics and Policy*, 14: 275–295

Nelson, R. R. and Winter, S.G. 1982. *An Evolutionary Theory of Economic Change*. Cambridge, MA: Harvard University Press.

Nooteboom, B. 2000. Learning by interaction, absorptive capacity, cognitive distance, and governance. *Journal of Management and Governance,*4: 69–92.

Norton, E.C., and Wang, H., Ai, C. 2004. Computing interaction effects and standards errors in logit and probit models. *Stata Journal,*4(2): 154–167.

OECD, (2009), Guide to Measure Information Society.

Pe'er, A., and Vertinsky I. and King, A. 2008. Who enters, where, and why? The influence of capabilities and initial resource endowments on the location choices of de novo enterprises. *Strategic Organization*. 6(2): 119-149.

Porter M. E. 1990. *The Competitive Advantage of Nations*. New York: Free Press.

Porter, M. E.1998. *On Competition.* Boston: Harvard Business School Publishing.

Pouder, R., and St. John C. H. 1996. Hot spots and blind spots: geographical clusters of firms and innovation. *Academy of Management Review,* 21(4): 1192-1225.

Powell, W.W., Koput, K. and Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*, 41: 116-145.

Ramani, S. V. and De Looze .M. A. 2002.Using patent statistics as knowledge base indicators in the biotechnology sectors: An application to France, Germany and the U.K. *Scientometrics.* 54(3): 319-346.

Romer, P. M. 1986. Increasing Returns and Long-run Growth. *Journal of Political Economy* , 94(5): 1002-37.

Rosell, C. and Liu, R., (2011). Import Competition, Multi-product Firms, and Basic Innovation. Working paper.

Rosenkopf, L. and Nerkar, A. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disc industry. *Strategic Management Journal*, 22 (4): 287-306

St. John, C. H. and Pouder, R. W. 2006. Technology clusters versus industry clusters: Resources, networks, and regional advantages. *Growth and Change*, 37(2): 141-171.

Stuart, T., Sorenson, O. 2003. The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research Policy,*32: 229–253.

Sutaria, V. and Hicks, D. A. 2004. New firm formation: dynamics and determinants. *The Annals of Regional Science*, 38: 241–262.

Train K. 1986. *Qualitative choice analysis: theory, econometrics, and an application to automobile demand*. Cambridge, MA: MIT Press.

Wang C. and Lin C.S.2008. The growth and spatial distribution of china's ICT industry: New geography of clustering and innovation. *Issues & Studies,*44 (2): 145-192.

3. KNOWLEDGE BASE OF INDUSTRIAL CLUSTERS AND REGIONAL TECHNOLOGICAL SPECIALIZATION: EVIDENCE FROM ICT INUSTRIAL CLUSTERS IN CHINA

3.1 ABSTRACT

This study intends to understand the underlying structure and composition of an industrial cluster and explains why certain types of technology appear to blossom and fade in a region over time and sheds light on the question about driving forces behind the evolution of industrial clusters that has long been puzzling. Taking the perspective of technology system this study explores the influence of knowledge centrality of a technology on regional technology specialization (RTS) by taking into account inter-regional effects of the knowledge characteristics and the moderating role of technology markets. Based on the patent data from State Intellectual Patent Office (SIPO) and regional level data of five regions concentrated with ICT industrial clusters in China, dynamic panel regression using difference GMM is adopted to test the hypotheses. The results show that the knowledge centrality of a given technology in the focal region has negative impact on focal RTS and this relationship is not affected by the development of local technology market. Instead, the knowledge centrality of the technology in other ICT regions, on average, has negligible effect on focal RTS but this relationship highly depends on the development of technology market in the other regions. The moderating effect of the technology market is found to be negative and significant.

Key words: regional technology specialization, knowledge centrality, and technology market

3.2 INTRODUCTION

Industrial clusters have shown significant influences on the regional performance in terms of growth of employment, wages, establishments and innovation activities due to the agglomeration externalities that are derived either from specialized or diverse economic activities in the region. The structure and composition of an industrial cluster is not given but changes over time. The dynamics underpinning regional performance however has not been fully understood. There are few studies that have examined what are the drivers behind the evolution of the cluster and how the co-location patterns of different industries such as industrial specialization or diversification change over time (Delgado, Porter and Stern, 2011).

Among studies that have paid attention to the determinants behind the dynamics of industrial cluster, some have examined the role of industrial relatedness within a region through affecting the nature and scope of knowledge spillovers in the region (Boschma and Frenken, 2009). Boschma (2004) has shown that once a region specializes in a particular knowledge base, it will act as incentives offering opportunities to local firms for further improvement in familiar knowledge and discourage knowledge creation that does not fit the regional knowledge base. Neffke and Henning (2008) have shown that sectors related to other sectors in the regional portfolio are more likely to enter the region as compared with unrelated sector that are likely to exist the region. Regions showed a high degree of technological coherence between the set of industries over time. Malerba and Montobbio (2003) have shown that international technological specialization of a country is highly path dependent and persistent and it is affected by knowledge spillovers across interdependent sectors within countries. In sum, these studies claim that there is spatial path dependence that is driven by the existing related activities in a region. The rise and fall of industries in a region are conditioned by regional industrial structure in the past and the profile of industries and technologies tends to be stable (Neffke, 2009).

Existing regional studies have treated regions in isolation by focusing mainly on the factors within a region and their impacts on regional performance and dynamics. They have neglected largely inter-regional effects, meaning the interactions between different regions with similar or different characteristics (Zhang, Li and Schoonhoven, 2009). However, as Porter (1998) and some other scholars (e.g. Henderson, 2005; Zhang, et al., 2009) have posited, an industrial cluster could affect the productivities of other clusters in many important ways. The presence of a strong cluster in the other regions can be the source of local competition, especially when resources are limited (Delgado, et. al., 2011). The knowledge flow between related industries is not restricted to a region but will also be manifest between neighboring or connected regions (Neffke, Henning and Boschma, 2009). Therefore, it is important to understand this inter-regional dynamics while carrying out regional studies. Being one of the clusters that specialize in certain industries, the development of this cluster is likely to be influenced by other clusters with similar industrial portfolio and located in different regions within a broader geographical area such as within a country.

In the current study, I argue that the inter-regional relationships between different geographical regions that specialize in ICT industry have substantial influence on the development of the industrial clusters. I investigate and explain why some technologies appear to blossom and fade in certain regions over time and try to make a contribution to the literature by taking into account the inter-regional effects. Specifically, this study explores the influence of the knowledge base of industrial clusters in both the focal and the other ICT regions on the regional technological specialization (RTS) of a given technology in the focal region. Previous studies carried out at the region, cluster or industry level have not disentangled the various driving forces behind the regional economic activities. This study makes analysis at the level of industrial region, which is an appropriate choice especially when the study is conducted within the social context of China. This is because regional economic development and local firms business activities are effectively influenced and sometimes even directed by local government policy measures. China as a transitional economy has been going through an economic reform from a centrally planned economic system to a free market since 1978. During this course, part of the transition occurred through giving local governments more autonomy by central authority. Local government thus retains considerable power and government policy and intervention still plays an important role in many aspects of regional social and economic activities. For example, local officials are motivated to encourage and protect local firms and their business. Sometimes they would maximize their own benefit even if it were not for the interest of the country as a whole (Khanna and Oberholzer-Gee, 2006).

This study views an industrial cluster as a *technological system* which is defined as a dynamic network of agents interacting in a specific economic/industrial area and involved in the generation, diffusion, and utilization of technology (Carlsson and Stankiewicz, 1991). The unit of observation for this study is technology. This is because the production and function of products are based on technologies, and most products use a variety of technologies (Schmoch, 2008). It is the fundamental constituent part of industry and forms the basis for industrial development. In addition to acknowledging the technology imperative, this study takes into consideration the roles played by institutional factor such as the development of technology market in determining regional technology specialization.

Technological knowledge flows through two different mechanisms (Maggioni and Uberti, 2007): the unintended knowledge spillovers and the intended knowledge transfers. The composition and structure of the knowledge base of a cluster affect the nature and scope of knowledge flow. I theorize that the knowledge centrality of a given technology in both the focal and the other ICT regions' knowledge base negatively influences the focal RTS but through different mechanisms. The knowledge centrality of a given technology is defined as the number of connections this technology has with other technological fields and it influences the scope and magnitude of knowledge spillovers across these different but related knowledge domains.

For a given technology, the negative relationship between its knowledge centrality and regional technology specialization in the focal region is in large part driven by the effective communication between different knowledge domains and the emergence of new technological opportunities due to the prevailing localized knowledge spillovers across various related application fields. While the relationship between other ICT regions' knowledge centrality and the focal RTS of a given technology is largely determined by varying demand for this technology in the focal region, which is realized through intended knowledge transfer across these regions.

Technology market is designed to promote technology exchange and balance the disequilibrium between technology sources and industrial demand. It plays a key role in facilitating knowledge flows both within and across regions and driving the regional labor division and specialization. With the development of the focal technology market, the negative effect of focal region's knowledge centrality of a given technology on the focal RTS is attenuated due to the increasing demand for this particular technology from both the focal and other ICT regions. In this case, for most firms active in the given technology field serving as specialized technology suppliers and engaging in the technology trade with others are likely to be more profitable than to diversify into many related technological fields and exploit all the possible applications by themselves. When the development of the technology market in the other regions is more advanced, the technology supply of other regions is getting more effective and efficient. This can intensify the negative relationship between the other ICT regions' knowledge centrality and focal RTS due to the increasing reliance of the focal region on the technology well supplied by the other regions and the subsequent reduction of its own investment on this particular type of technology.

Based on the patent data from the State Intellectual Property Organization of China (SIPO) and regional level data of five regions concentrated with ICT industrial clusters in China I adopt dynamic panel regression using difference GMM to test the proposed hypotheses. The results show that, both the focal and other ICT regions' knowledge centrality of a given technology have impact on the technology specialization of the focal region. The former relationship theorized to be driven by the prevalence of localized knowledge spillovers is not moderated by the development of the local technology market. The latter one that is hypothesized to be driven by the intended knowledge transfer is highly influenced by the development of the technology market in other ICT clusters located in geographically distant regions.

The rest of the paper is organized as follows. I briefly review the background literature. Thereafter, I develop theoretical arguments leading to the hypotheses, explain the research methodology, present the results and close the study with a discussion of the findings, limitations and avenues for the future research.

3.3 BACKGROUND

3.3.1 Characteristics of Regional Knowledge Base

Within an industrial cluster, various types of knowledge with distinctive nature from different technology fields are pooled together. The features of local knowledge such as the variety of the components within the knowledge base and the relatedness among these different types of knowledge in a cluster are considered to have very important implications for the innovation activities, economic performance and the convergence or divergence of a region through impacting the nature and the scope of knowledge spillovers within the region (Bae and Koo, 2008; Boschma and Frenken, 2009).

To better understand and capture the relationship and interaction between different technology domains, Ramani and Looze (2002) define knowledge base as a collection of the technological knowledge that an agent (i.e. an individual, institution, a region or a nation) possesses. Based on patent statistics, they introduced several attributes to characterize the knowledge base of a geographic location, among which

knowledge centrality is defined as the number of connections of a given technology has with other technological fields. It is measured by the number of technology classes with which the given technology has been co-classified in patent applications. Based on the applicability to practical fields, every patent is attributed to one main and several, if any, supplementary technology classes by the national/local patent office according to the IPC classes, which is an internationally agreed, non-overlapping and comprehensive patent classification system. Technology affiliation to one or more technological fields is assigned if the technology can be applied into these fields and the technological fields are therefore related with each other.

This attribute of the knowledge base is particularly useful to understand the components and the structure of the industrial cluster and its dynamics as it indicates the relatedness of the focal technological knowledge with other knowledge domains. The extent to which knowledge domains are connected with each other will influence the way knowledge flow both within and across geographically distant industrial regions. According to the definition and measure, higher knowledge centrality of a technology implies that there are potentially more application fields in which the technology could be used and there are more opportunities and possibilities for firms to enter diverse technology fields. This will have important implications for the technological and industrial evolution in a region.

3.3.2 Mechanisms of Knowledge Flow

To understand the characteristics of regional (focal region and other regions) knowledge base influence focal region's technology specialization we should look at first two different mechanisms through which technological knowledge flows (Maggioni and Uberti, 2007): the intended knowledge transfer such as imports of capital goods, direct investment and technology trade; and the unintended knowledge spillovers via various mechanisms such as the professional associations, social relationships, shared scientists (Zucker et. al., 1998), spin-offs and labour mobility (Neffke, Henning and Boschma, 2009).

Due to the tacit nature of knowledge, unintended knowledge spillovers tend to be more prevalent in the geographically bounded area than between geographically distant regions. Meanwhile, firms are familiar with the local conditions such as the market, social relations, rules and regulations, etc., which give firms more incentive and make it easier to acquire and apply technologies with potential of commercialization. From the viewpoint of the focal region, the level of knowledge centrality of a given technology in the region drives unintended knowledge spillovers through the channels formed according to the structure of local knowledge base. Knowledge centrality also depicts the profile of potential application fields of a technology, which will potentially give rise to the downstream markets. This will influence the demand for this technology and the level of competition and complementarity among regions concentrated with similar industrial clusters, which in turn drives the intended knowledge transfer across these regions.

3.4 THEORETICAL DEVELOPMENT AND HYPOTHESES

3.4.1 Conceptual Model

I present in **Figure 4** the conceptual model of this study. The focus is first on the relationships between the focal and other the ICT regions' knowledge centrality of a given technology on the focal region's technology specialization. Then the focus shifts to the development of the technology market in both the focal and the other regions and see the extent to which technology market moderates the previous relationship. In the model, the **Focal RTS** stands for the regional technology specialization of a given technology in the focal region. The **Focal and Other Knowledge Centrality** stands for knowledge centrality of a given technology in the focal and the other regions respectively. The **Focal and Other Technology Market** stands for the development of technology market in terms of total value of the technology contract deals in the focal and the other ICT regions respectively.

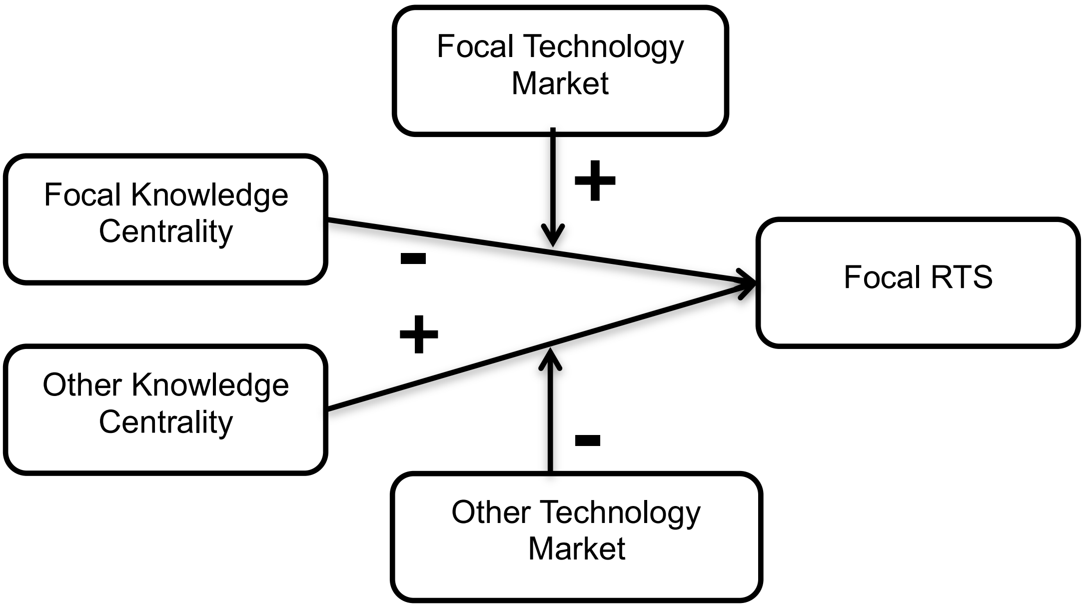

FIGURE 4 CONCEPTUAL MODEL

3.4.2 Knowledge Centrality and Regional Technology Specialization

Studies in the economic geography literature investigating regional growth paths have demonstrated that regions are most likely to branch into new industries that are technologically related to the existing industries in the region (Neffke, Henning and Boschma, 2011). This happens because the diversified economic activities drive division of labor, increase efficiency and most importantly give rise to the opportunities of innovation within a region (Jacobs, 1969; Neffke, et. al., 2009). This is a learning process that is largely driven by the knowledge flows among different industries or knowledge domains in question through various channels. It has been found that there exists an optimal level of cognitive distance (neither too close nor too distant) between these diversified but related industries that can facilitate the effective communications among different knowledge and boost the emergence of new opportunities in the region.

In a technology system, firms from focal region perceive higher levels of knowledge centrality of a given technology in the local knowledge base as greater number of technological opportunities on the one hand. On the other hand, higher levels knowledge centrality also means that there are higher probabilities of knowledge spillovers. This is because higher levels centrality of a given technology indicates that this technology is extensively related with other technological fields in the local knowledge base. Through this well-connected knowledge network a circulation and transfer of related technological knowledge takes place. This will make firms in the region open to other knowledge sources and increase the possibility to broaden the scope of search in responding to the potential technology opportunities. Firms integrate knowledge they receive from different domains and eventually are more likely to explore various technology areas that are related to but different from the one in question.

Moreover, firms located within a region are familiar with the local conditions such as the market, social relations, rules and regulations, etc. They tend to know and get to know each other better and easier in comparison with firms located in distant areas. The probability to learn from each other is also higher due to more frequent formal and informal contacts with each other. Firms experience more intense knowledge spillovers and larger pool of discoveries and ideas from related technological fields with higher levels of diversity than that might be true for technological fields characterized by lower levels of knowledge centrality. So I propose that:

> ***Hypothesis 1 (H1): Regional technology specialization is negatively associated with the knowledge centrality of this technology in the knowledge base of the focal region.***

Now we start looking at how the knowledge centrality drives knowledge flow across geographically distant regions that have similar industrial portfolio (ICT industry in the current case) and the impact of other region's knowledge centrality on the focal region's technology specialization. I propose that knowledge centrality of a technology in the other regions positively influences the focal RTS.

Due to the tacit nature of knowledge, unintended knowledge spillovers tend to be more prevalent in the geographically bounded area than between distant regions (Jaffe, Trajtenberg and Henderson, 1993). Firms located in different geographically distant regions can't easily rely on the convenient informal, face-to-face mechanisms of commutation (Tallman and Phene, 2007) therefore it is difficult, if not impossible, to receive knowledge spillovers from regions that are located far away from them. When knowledge centrality of a technology in other regions is high, although there will be technological opportunities emerging from wildly connected knowledge domain, focal region in this case is less likely to have access to intensive knowledge spillovers even though they are fully aware of the increasing level of applicability of the technology due to the difficulties associated with long-distant knowledge spillovers across regions.

The knowledge centrality of a technology in the other regions therefore gives rise to the competitive tension between the focal and other regions. Specifically, increases in the knowledge centrality of a given technology means there will be more application fields to which this technology could be applied and if applied successfully it will give more access to the downstream markets. This is very attractive to firms in regions with similar industry and technology portfolio because they can easily recognize and realize the value associated with the technology as the cognitive distance between them is relatively close. This will lead to the increases in demand for this technology from the focal region. Moreover, regions specialized in the same industry are naturally compete with each other for the allocation of various resources at national level. Regions would not like to be lagged behind in developing technologies with great commercial potential. This competitive reactions will drive focal region invest more in the technology field in question, which will subsequently increase focal RTS. As a consequence, the technology specialization in the focal region increases gradually. So I propose that:

Hypothesis 2 (H2): Regional technology specialization is positively associated with the knowledge centrality of the same technology in the knowledge base of the other regions.

3.4.3 Moderating Role of Technology Market in the Focal and Other Regions

A technology can be obtained through investing in R&D and developing this technology by oneself or purchasing the technology from others via technology market which is an institution designed to promote technology exchange in order to balance the disequilibrium between the technology sources and industrial demand (Arora and Gambardella, 2010; Johnson and Liu, 2011). In the current study I adopt the definition provided by the State Science and Technology Commission (SSTC), which defines technology market as the various forms of technological trading activities, such as the transfer of scientific achievement, technical consultancy, training, service, contracts, joint technical operations and partnership research-production corporations. This definition has also been adopted by some other studies (e.g. Johnson and Liu, 2011).

Technology market is a place where exchange activities such as buying, selling and licensing of technology and related service between different parties take place in both intra-regional and inter-regional setting. The technology transfer aspects associated with technology market increases the efficiency of technology development across regions. Firms within a region can chose to develop a technology by themselves or buy the technology from others. The development level of technology market can therefore be complementary or substitute to a region's effort devoted into the development of a certain technology depending partly on the development level of technology market in local and other regions, which consequently influences regional technology specialization.

From the perspective of the focal region, technology market in the region serves as a channel linking effectively the suppliers of the technologies in the focal region and the users of them from both the focal and other regions. Firms in the focal region that are active in these technologies can act as specialized technology suppliers thanks to the development of the technology market in this region. Considering the economies of scale in production and limit of resources in a region, for firms in the focal region, technology trade is likely to be more efficient than exploiting all potential applications of their technology by themselves. Given a certain level of knowledge centrality of a technology in the focal region, the more advanced the local technology market is, the more effective communication and interaction between technology suppliers and users are, therefore the specialization of this technology in the focal region will be higher. So I propose that:

> ***Hypothesis 3 (H3): The negative relationship between regional technological specialization and knowledge centrality of a given technology in the focal region is attenuated by the development of the technology market in the focal region.***

As we discussed before, higher knowledge centrality of a technology indicates broader areas in which this technology could be applied. When the knowledge centrality of a given technology in other ICT regions increases, firms in the focal region perceive the potential opportunities brought by this technology and the necessity to adopt it. Since in the current case focal region would suffer from the difficulties in accessing to the knowledge spillovers in other regions which located far away, firms in the focal region then should resort to other solutions. One of the choices would be to access the technology through other mechanisms facilitating intended knowledge transfers across these regions such as imports of capital goods, direct investment and technology trade, if there is any. Then whether or not and the extent to which local firms could access and utilize this technology will be influenced by the channels that link these regions and influence the intended knowledge flow between regions.

Technology markets in the other ICT regions serve as a channel connecting the demands and supplies of the technology between the focal and other regions. The higher the development level of technology market the more effective and efficient the technology trade via the market. Given a certain level of knowledge centrality of a technology in the other ICT regions, the higher the development level of the other regions' technology markets the easier and more efficient firms in the focal region could acquire this technology from other regions through technology trade across regions. This will increase the reliance of focal region on the technology supplies from other regions and subsequently decrease the investment of indigenous research and development in this technology by firms within the focal region. In the end, the specialization and competitiveness of the given technology in the focal region decreases mainly due to the increased efficiency caused by external technology suppliers from other ICT regions. So I propose that:

> ***Hypothesis 4 (H4): The positive relationship between regional technological specialization and knowledge centrality of a technology in the other regions is attenuated by the development of the technology markets in the other regions.***

3.5 METHODS

3.5.1 Research Setting

I investigate the research questions in the context of Information Communication Technology (ICT) industry in China during the period between 1985 and 2009. ICT industry is chosen as a representative example of high-technology industries as the knowledge spillovers and transfer play an important role in firm's innovative activities and regional technology specialization. China's ICT industry has experienced rapid growth sine 1990s. It is becoming the most dynamic sector in China's economy and attracting increasing attention from both the academic and business world (Meng and Li, 2002; Wang and Lin, 2008).

ICT industry in China is geographically uneven at the national level. According to the Employment Location Quotient and the share of patent applications in the ICT industry of 31 regions (provinces, autonomous regions, municipalities) in China, there are five regions turn out to be highly concentrated with employment and patent applications of ICT industry. They are Beijing, Shanghai, Jiangsu, Guangdong and Shaanxi. The recent observations from the ICT clusters in China have shown that the patterns of technological specialization of industrial regions actually are more sophisticated than that has been documented in the existing literature. For example, when we look at the regional technology specialization of five regions (i.e. provinces) with the concentration of ICT industry in China, we see that there exist significant increase and decrease in terms of regional technology specialization along some technological fields in a region over time. Surprisingly and interestingly, the changing pattern of specialization of a given technological field in one region is accompanied by the opposite changing pattern of specialization of the same technological field in other regions. These phenomena are have not been investigated nor explained well by the existing theories.

3.5.2 Data and Sample

The data used in this study are the patent applications obtained from the State Intellectual Property Office (SIPO) in China. China joined the World Intellectual Property Organization (WIPO) in 1980 and adheres to most of the international patent agreements (e.g. the Paris Convention, the PCT and the TRIPS). China implements laws for all relevant IPRs such as patents, trademarks and copyrights. According to the patent law, patents can be granted to inventions that fulfill the requirements: novelty, inventiveness and practical applicability, which are comparable to the regulations of other important foreign and international patent offices. SIPO is the governing body and directly affiliated to the State Council with main responsibilities such as organizing and coordinating IPR protection nationwide, standardizing the basic orders of patent administration, drawing up the policies of foreign-related IP work etc. All IPRs are filed directly at SIPO or it's branches that are responsible for the acceptance, examination and publication of all IPR related documents. After a patent application has been filed it will be classified according to the International Patent Classification (IPC) by patent examiners (The guideline of patent classification is discussed in the response to the question regarding the main and secondary classifications). Applicant may request a substantive examination of the patent within three years after the filing date. If the invention (after notified amendment) is not in line with Chinese patent law, the application will be rejected. Applications that meet the legal requirements of patentability will be granted and the patent right will be effective for up to 20 years after the priority date. Any party could ask the SIPO Patent Re-Examination Board to invalidate a granted patent.

This database covers 4,084,530 patents (include 1,610,798 invention, 1,373,542 utility model and 1,100,190 design) received by SIPO from 1985 (SIPO's first year of activity) to 2009 by firms, institutions and individuals from any country seeking legal protection for their innovations. SIPO discloses the following information regarding each patent: application number, publication number, application date, publication date, priority information, international classification, applicant(s) name, applicants address, inventor(s) name, patent agency code, patent agent and abstract of the patent. Regional-level data of Beijing, Shanghai, Jiangsu, Guangdong and Shaanxi from 1990 to 2009 is obtained from the China Statistical Yearbook on Science and Technology, the Industrial Economy Statistical Yearbook of China and the regional Statistical Yearbook.

Starting with the patent applications in the five regions concentrated with ICT industrial clusters from 1985 to 2009, and 60 technology classes (International Patent Classification, 8th edition, 2006) of ICT industry that belong to 4 sub-sectors (Telecommunications, Consumer electronics, Computers, office machinery and Other ICT), I identify all ICT patents based on the IPC codes. Every patent is attributed to one main and several, if any, supplementary technology classes by the national patent office according to IPC classes, which is an internationally agreed, non-overlapping and comprehensive patent classification system. Technology affiliations to one or more technological fields are assigned by SIPO to each patent and it will be indexed by j or k = 1, 2, … m. There exists a vector with m components. A component takes value 1 if the patent is affiliated to the corresponding technology and 0 otherwise. In this study, the knowledge base of Shanghai ICT cluster can thus be represented by the following matrix $\mathbf{M}_\mathrm{i}$:

$\mathrm{M_i} = \begin{bmatrix} f_1^i & c_{12}^i & \cdots & c_{1m}^i \\ c_{21}^i & f_2^i & \cdots & c_{2m}^i \\ \vdots & \vdots & \ddots & \vdots \\ c_{m1}^i & c_{m2}^i & \cdots & f_m^i \end{bmatrix}$, in which the technology vector of technology k in the knowledge base of region i (ICT cluster in the current case) is: $c_{k1}^i, c_{k2}^i, \ldots, f_k^i \ldots, c_{km}^i$, k ∈ [1, m] and c_{kl}^i is the number of patents that are affiliated both to technology k and l in region i from 1985 until a certain year t.

3.5.3 Variables and Measures

Dependent Variable: the dependent variable in the current study is the ***Regional Technology Specialization***[3]*, which* is the distribution of a region's patents

---

[3]There are also other measures of technology specialization. For example, an often used index is "revealed technological advantage" which can be defined in the current case as a region's share of patents in a particular technology field divided by the region's share of patents in all patent fields within the country. However, it cannot serve the purpose of this paper as it indicates the relative specialization of a given region in a selected technological domain, which means that there can be cases that even though the absolute value of concentration of the given technology increases, the region could still be comparatively less specialized in this technology field and vice versa.

(technologies employed) over various technology fields in the industries within the region. A region's technology specialization in a selected technology field is measured by the share of patent applications from the technology field in the total patent applications of the region by the year of observation and log transformed (Van Zeebroeck, Van Pottelsberghe de la Potterie, and Han, 2006):

$RTS_i = \frac{p_i}{\sum_i^n p_i}$, Where $\mathrm{p_i}$is the number of patents applications of a region in the $\mathrm{i^{th}}$ technology field with i =1..., n, where n is the total number of technology fields in the region. The more concentrated the patents are in a certain technology field, the higher the value of concentration is and the more the region is said to be specialized in this technology field.

Independent Variable: the independent variable in this study is the ***Knowledge Centrality*** of a technology in the knowledge base of the focal and the other ICT regions. It indicates the relatedness of a technology with other technology fields. The centrality of a technology in a focal ICT region is measured by the number of technology classes with which this technology is co-classified in the patents in this region filed until one year prior to the observation and log transformed. The knowledge centrality of a technology in the other ICT regions is obtained by taking the average value of knowledge centrality of these regions.

Moderating Variable*:* the moderating variable in this study is the ***Technology Market*** which is defined as an institution designed to promote technology exchange in order to balance the disequilibrium between the technology sources and industrial demands (Johnson and Liu, 2011). It is measured by the total value of technology contract deals[4] of a region as a technology supplier, meaning that the contract deals

[4] Technology contract normally includes 4 types: Technology Development, Technology Transfer, Technology Consultation and Technology Service.

in a region's technology market includes deals among firms within the region and the outflow of deals from the focal region to the other regions. The measure of technology market of the other regions is obtained by taking the average value of the total contract deals in the technology markets of the other regions.

Control Variables*:* to test these hypotheses, I also control for alternative explanations for regional technology specialization at the regional level. ***Science and Technology Personnel*** is measured by the total number of personnel that work in the fields pertaining to the development of science and technology and log transformed in the prior year of observation. ***Export*** is measured by the total value of export sales of all firms within a region in the prior year of observation. ***Foreign Direct Investment (FDI)*** is measured as capital invested in a region by sources not from China. ***GDP*** is measured by the gross domestic productivity at the regional level. ***Higher Education Institution*** is measured by the total number of colleges and universities in the region. These variables were all updated annually and log transformed in the prior year of observation. Furthermore, I control for time effect by adding ***Year*** dummies. I include the focal and the other regions' ***Technology Specialization lagged*** with one year to the model on account of the path-dependent nature of technology evolution (Arthur, 1994; David, 1988).

3.5.4 Econometric Models

The econometric model of this study is the following:

$$\begin{aligned}\mathrm{RTS}_{i,j,t} = {} & \beta_1 \mathrm{FKC}_{i,j,t\text{-}1} + \beta_2 \mathrm{OKC}_{i,j,t\text{-}1} + \beta_3 \mathrm{FMKT}_{i,j,t\text{-}1} + \beta_4 \mathrm{OMKT}_{i,j,t\text{-}1} + \\ & \beta_5 \mathrm{FKC}_{i,j,t\text{-}1} \times \mathrm{FMKT}_{i,j,t\text{-}1} + \beta_6 \mathrm{OKC}_{i,j,t\text{-}1} \times \mathrm{OMKT}_{i,j,t\text{-}1} + \\ & \beta_7 \mathrm{RTS}_{i,j,t\text{-}1} + \beta_8 \mathrm{ORTS}_{i,j,t\text{-}1} + \beta_9 \mathrm{Year}_t + \beta_{10} \mathrm{X}_{i,t\text{-}1} + \varepsilon_{i,j,t},\end{aligned}$$

where subscript i=1, 2, …N refers to the region and its maximum value is 5. Subscript j =1, 2…N refers to the technology class of ICT industry and its maximum value is 60. Subscript t =1, 2…T refers to the year and its maximum value is 24. RTS/ORTS, FKC/OKC and FMKT/OMKT refer to the regional technology specialization, the knowledge centrality and the technology market of the focal and the other region respectively. $X_{i,t}$ refers to a set of control variables. All variables are transformed with logarithm.

An autocorrelation problem appears due to the inclusion of the lagged term of RTS, which is dependent upon the past disturbances. Knowledge centrality is likely to be endogenous due to the potential correlation with the current and past error terms. I adopt the first differenced generalized method of moments (Difference GMM) estimation, which is firstly introduced by Arellano and Bond (1991) for dynamic panel data in order to deal with simultaneously the problem of the endogenous independent variables, the heteroskedasticity and autocorrelation within individuals. Being aware of the caveats of this method, robustness test is carried out with the number of instruments being properly controlled by limiting the number of lags used in GMM instruments on account of instrument proliferation.

3.6 RESULTS

Descriptive statistics and correlations of the variables are presented in Table 8. The correlation matrix shows that regional GDP is highly correlated with regional export, FDI and the number of higher education institutions, indicating that regions with higher level of economic development also tend to export more and attract more foreign investments. The high correlation between the regional technology specialization of the current year and the last year indicates the path dependent nature of the regional technology development.

TABLE 8 DESCRIPTIVE STATISTICS AND CORRELATIONS OF THE VARIABLES

	1	2	3	4	5	6	7	8	9	10	11	12
Mean	0.003	0.003	0.003	0.000	0.000	0.000	0.091	7.861	12.138	13.695	2.601	4.000
Std. Dev.	0.009	0.009	0.007	0.378	0.352	1.377	1.125	1.298	0.510	1.893	1.876	0.396
Min	0.000	0.000	0.000	-0.268	-0.346	-2.793	-2.162	5.198	9.649	9.246	-2.128	3.367
Max	0.160	0.160	0.070	3.268	3.408	3.250	2.115	10.513	13.176	17.518	5.526	4.990
1Focal RTS	1.000											
2Lag focal RTS	0.990	1.000										
3Lag other RTS	0.732	0.739	1.000									
4Focal knowledge centrality	-0.157	-0.158	-0.147	1.000								
5Other knowledge centrality	-0.228	-0.227	-0.278	0.227	1.000							
6Focal technology market	0.119	0.113	0.100	0.033	-0.128	1.000						
7Other technology market	0.123	0.118	0.147	0.046	-0.185	0.616	1.000					
8 Focal GDP	0.120	0.115	0.105	0.006	-0.143	0.662	0.784	1.000				
9 Focal sci.& tech. personnel	0.095	0.098	0.076	0.031	-0.105	0.667	0.417	0.548	1.000			
10Focal export	0.113	0.109	0.079	-0.039	-0.112	0.635	0.573	0.909	0.489	1.000		
11Focal FDI	0.080	0.075	0.055	-0.002	-0.079	0.601	0.477	0.881	0.480	0.911	1.000	
12Focal University	0.117	0.116	0.126	0.044	-0.166	0.622	0.805	0.785	0.692	0.583	0.527	1.000

The results of estimating the focal regional technology specialization are presented in Table 9. Model 1is the baseline model including only the control variables. Model 2 is used to test Hypothesis 1 and Hypothesis 2, which concern the relationship between the knowledge centrality of a given technology in the focal and the other ICT regions and the technology specialization of this region (focal RTS). Model 3 includes the main effects of technology market of the focal and other regions. Model 4 is the full model including the interaction terms of knowledge centrality and technology market of the focal and the other regions in order to test Hypothesis 3 and Hypothesis 4, which focus on the moderating role of the technology market on the relationship between knowledge centrality and RTS.

For each regression, Arellano and Bond test for the first and second order serial autocorrelation is calculated. As it is shown in Table 9, Arellano-Bond AR(1) is found to be negative and significant at 0.01 level, while the Arellano-Bond AR(2) is not significant meaning that there is no second order correlation. Hansen test for the over identification is calculated and the null hypothesis cannot be rejected which indicates the validity of the instruments in the difference GMM estimation. All models are significant at the 0.001 level.

The results in Model 2show that, knowledge centrality of a given technology in the focal region has significant negative main effect (-0.0004) on focal RTS at 0.01 level. The economic meaning of the result can be understood as other things being equal, for any 50% increase in the focal regional knowledge centrality of a given technology we would expect about 0.016%[5] decreases in focal regional specialization in the

[5]Because both the dependent variable and the independent variables in the analysis are log-transformed (expect dummy coded variables), I interpret the coefficient (β) of key explanatory variable as the elasticity between x (the independent variable) and Y (the

given technology. Hypothesis 1 predicts that focal RTS is negatively associated with focal knowledge centrality is therefore supported. On average, knowledge centrality of a given technology in the other regions has negligible effect (0.0002 but not significant) on focal RTS. When the value of technology market in the other regions is fixed at its mean, the effect of knowledge centrality of a given technology in the other ICT regions turns out to be significant and negative (-0.0004) at 0.1 level. In other words, when the value of technology market in other ICT regions is fixed at its mean, for any 50 % increase in the knowledge centrality of a given technology in other ICT regions, we will expect about 0.016% decreases in focal regional specialization in the given technology. Hypothesis 2 predicting that focal RTS is negatively associated with other knowledge centrality is partly supported.

The results in Model 4 show that, the interaction effect (0.00002) of knowledge centrality of a technology and the development of technology market in the focal region on the focal RTS is not statistically significant, thereby providing no support for Hypothesis 3 which predicts that the negative relationship between focal RTS and focal knowledge centrality is attenuated by the development of the focal technology market. However, it is worth noting that focal technology market has a direct positive effect (0.0005) on the focal RTS at 0.01 level which means when keep other factors constant, any 50% increases in the total value of contract deals in focal technology market will lead to 0.02% increases in the level of focal region's technology specialization. The interaction effect of knowledge centrality of a given technology and the development of technology market in the other ICT regions on the focal RTS is statistically significant and negative (-0.0005). Hypothesis 4 predicting that the negative relationship between RTS and the knowledge centrality in the other regions

---

dependent variable):y(x2)/y(x1) = (x2/x1)^β. So, when focal knowledge centrality increases by 50%, the expected percentage change in RTS is therefore ((1+0.5)^(-0.0004)-1)= 0.016%.

is intensified by the development of technology market in the other regions is supported.

To elaborate further the negative moderating effects of the technology market, I represent it graphically in Figure 5 by plotting different regression lines of focal RTS on knowledge centrality of a given technology at three different levels of the technology market in the other regions, low level (minus one standard deviation from the mean), medium level (mean value of technology market) and high level (plus one standard deviation from the mean). As it is shown in Figure 5, the effect of knowledge centrality of the other regions on focal RTS depends on the development level of their technology market. When the development level of technology market in the other regions is high or medium, their knowledge centrality negatively influence the focal RTS. However, when the development level of technology market in the other regions is low, their knowledge centrality is positively associated with the focal RTS.

Some of the control variables such as the lag term of focal and other region’s technology specialization, regional GDP and year dummies also show significant and positive effects on the focal RTS.

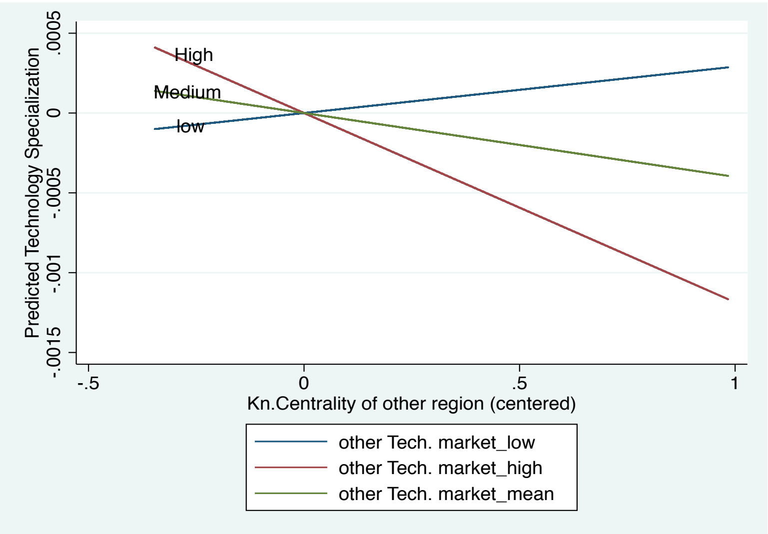

FIGURE 5 INTERACTION EFFECTS BETWEEN OTHER KNOWLEDGE CENTRALITY AND OTHER TECHNOLOGY MARKET ON FOCAL RTS

TABLE 9 REGIONAL TECHNOLOGY SPECIALIZATIONS

(DYNAMIC PANEL REGRESSION USING DIFFERENCE GMM)

Focal tech specialization	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Coefficient	Coefficient	Coefficient	Coefficient
Focal knowledge centrality		-0.0004**	-0.0002†	-0.0002†
Other knowledge centrality		0.00002	0.0002	-0.0004†
Focal technology market			0.0005**	0.0005**
Other technology market			0.0011†	0.0008
Focal Kn. Cent X Focal Tech Market				0.00002
Other Kn. Cent X Other Tech Market				-0.0005**
Lag focal tech specialization	0.8157***	0.7806***	0.7767***	0.7746***
Lag other tech specialization	0.0953*	0.1102*	0.0924†	0.0839†
Focal GDP	0.0018*	0.0013†	0.0013	0.0013
Focal Sci. & Tech. personnel	0.0000	0.0000	0.0000	0.0000
Year_1990	0.0052*	0.0038		
Year_1991	0.0050*	0.0036	0.0093*	0.0084*
Year_1992	0.0045†	0.0032	0.0083*	0.0075*
Year_1993	0.0041†	0.0029	0.0075*	0.0068*
Year_1994	0.0036†	0.0026	0.0072*	0.0065*
Year_1995	0.0032†	0.0023	0.0066*	0.0060*
Year_1996	0.0029†	0.0021	0.0063*	0.0057*
Year_1997	0.0028†	0.0020	0.0058*	0.0053*
Year_1998	0.0028*	0.0020†	0.0054*	0.0050*
Year_1999	0.0025†	0.0018	0.0049*	0.0045*
Year_2000	0.0026*	0.0020†	0.0045*	0.0042*
Year_2001	0.0025*	0.0019†	0.0041*	0.0039*
Year_2002	0.0022*	0.0018*	0.0036*	0.0035*
Year_2003	0.0020*	0.0016*	0.0032*	0.0030*
Year_2004	0.0015*	0.0013*	0.0022*	0.0021*
Year_2005	0.0013*	0.0011*	0.0020*	0.0019*
Year_2006	0.0007*	0.0006†	0.0012*	0.0012*
Year_2007	0.0002†	0.0002	0.0005*	0.0005*
Number of Observations	5400	5389	4972	4972
Arellano-Bond test for AR (1)	-3.48**	-3.23**	-3.03**	-3.01**
Arellano-Bond test for AR (2)	-0.15	-0.05	-0.43	-0.42
Hansen test	297.89	297.08	293.78	293.14

*** p< 0.001, **p<0.01, *p<0.05, † p<0.1

3.7 DISCUSSION

Existing studies on the regional innovation and technology development have been mainly focusing on factors within a region. This study takes into consideration inter-regional effects and explores specifically the influence of the characteristics of the knowledge base of industrial clusters in both the focal and other regions on the development of the focal region's technology specialization and the moderating role of the regional technology markets.

As expected, from the viewpoint of the focal region, focal knowledge centrality of a given technology has negative effect on focal RTS meaning that increases in the level of knowledge centrality of a given technology in the focal region leads to the decreases of focal region's specialization in that particular technological field. This result is explained by the effective communication between knowledge domains and emergence of new technological opportunities driven by the prevailing localized knowledge spillovers across various but related application fields in which the given technology could apply. Firms within a region are tempted to enter these diverse fields by taking advantage of their technological capability and familiarity with the local conditions.

However, knowledge centrality of a given technology in the other ICT regions does not show the expected negative effect on focal RTS. This result can be understood by looking at the moderating effects of technology market at different development levels. Given the technology market in the other regions is more developed, increases in the knowledge centrality in the other ICT regions reduces the focal RTS. This is because the effective knowledge trade between the focal and other regions, which is supported by well-developed technology market, leads to the subsequent reliance of the focal region on the technology supply from other regions. The technology specialization of the focal region is reduced thereafter. Instead, when the development level of other technology market is low, higher knowledge centrality in the other regions surprisingly increases the focal RTS. This is probably because on the one hand, the demand of a given technology from the focal region increases due to the observation of the increasing knowledge centrality in the other regions and the realization of the increasing potential application fields in which this technology could apply. On the other hand, under-developed technology market can't provide sufficient support to the inter-regional technology trade. Under this circumstance, focal region may be forced to invest in and develop this particular technology by itself and the focal RTS is likely to increase. The main effect of other knowledge centrality therefore shows negligible effect on focal RTS as it is obtained by taking the average effect of other knowledge centrality over all the values of other technology market.

The development of the focal technology market does not moderate the relationship between the focal knowledge centrality and RTS. Instead, I observe that focal technology market has significant direct positive effect on RTS. The development of focal region's technology market serves as a channel linking effectively the technology supplier and user of any kind. This in turn drives technology specialization in the focal region regardless of the level of knowledge centrality of that technology. Moreover, after adding the focal technology market into the regression model (see Model 3) the effect of focal knowledge centrality on RTS is reduced from -0.0004 at 0.01 level to -0.0002 at only 0.1 level. This indicates a partial mediation effect of the focal technology market. The speculation is confirmed by the post hoc analysis, which regress focal knowledge centrality on the technology market of the same region.

As to the effects of control variables, path-dependent nature of technology development explains the positive effect of the lag term of focal region's technological specialization on focal RTS. Demonstration, imitation and duplication of industry or technology development across regions at the national level may explain the positive effect of lag term of other region's technological specialization on focal RTS.

Overall, the results of this study support the existence of inter-regional effects of knowledge centrality of a given technology on the development of technology specialization of a region. The hypotheses on moderating effects of technology market are also partially verified.

3.8 CONCLUSIONS AND IMPLICATIONS

This study explores the influence of the knowledge centrality of a technology in the knowledge base of industrial clusters in both the focal and other regions on the development of the focal region's technology specialization by taking into account inter-regional effects and the moderating role of the regional technology markets.

I argue that there exist two different mechanisms of knowledge flow, unintended knowledge spillovers and intended knowledge transfer. From the viewpoint of the focal region, both the knowledge centrality of a given technology in the knowledge base of the focal and other region have influences on the focal region's technology specialization, but through different mechanisms. Due to the tacitness of the technological knowledge, unintended knowledge spillovers tend to be more prevalent within the geographically bounded locations than across distant areas. Technology market which is designed to promote technology exchange in order to balance the disequilibrium between the technology sources and industrial demand plays a key role in driving the knowledge flow across regions. Based on Chinese patent data from SIPO and region-level data of five ICT industrial clusters in China, dynamic panel regression using "xtabound2" STATA command is adopted in order to deal simultaneously with the problems such as endogenous independent variables and the heteroskedasticity and autocorrelation within individuals due to the introduction of the lag term of the dependent variable.

The estimation results from the full model have shown that, focal region's knowledge centrality of a given technology has negative impact on RTS due to the prevalence of localized knowledge spillovers and this relationship is not moderated by the development of the focal technology market as it is the channel dedicated to promote the intended technology trade. Instead, other knowledge centrality on average has no influence on focal RTS but as soon as the technology market of other region is included in the model the relationship becomes negative and get intensified when the level of technology market increases. The results indicate that the effect of intended knowledge transfer on focal RTS highly depends on the development level of technology market in the other ICT clusters, which is a channel promoting the technology trade across regions.

There are several limitations of this study. The measure of focal and other technology markets is based on the total value of technology contract deals in a given region. It is not distinguished between technology fields or between different industries. Therefore, it is a measure containing noise that may misrepresent the moderating effect of technology market. However, according to regional statistical reports on the development of technology market of the five regions concentrated with ICT industrial clusters, the value of contract deals from ICT industrial account for about 30% to 40% of the total contract deals of the region over the observation period, which is the largest share compared with other industries. The dominating role of ICT industry in these regions reduces the concern on the measurement issue. Due to the lack of data, I do not able to detect the magnitude of the technology trade between different regions but adopted only the contract deals of a region as the supplier of technology, which assumes that regions have equal accessibility to the technology market of each other.

3.9 REFERENCES

Arellano, M. and Bond, S., (1991) Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, Review of Economic Studies, Wiley Blackwell, vol. 58(2), pages 277-97.

Arora, A. and Gambardella, A., (2010) Ideas for Rent: An Overview of Markets for Technology, Industrial and Corporate Change, Vol. 19 (3), 775-803

Arthur, W. B. (1994). Increasing Returns and Path Dependence in the Economy, University of Michigan Press, Ann Arbor.

Bae, J. and Koo, J. (2008). Information Loss, Knowledge Transfer Cost and the Value of Social Relations. Strategic Organization, 6 (3), 227-258

Boschma, R. (2004) Competitiveness of regions from an evolutionary perspective, Regional Studies 38(9): 1001-1014.

Boschma, R. and Frenken, K. (2009). Chapter for book H. Bathelt, M.P. Feldman and D.F. Kogler (eds.). Dynamic Geographies of Knowledge Creation and Innovation, Routledge, Taylor and Francis.

Carlsson, B. and Stankiewicz, R. (1991). On the nature, function and composition of technological systems. Journal of Evolutionary Economics, Vol. 1 (2): 93-118.

David, P. A. (1988). Path Dependence: Putting the Past into the Future of Economics, Technical Report No. 533, The Economic Series, Institute for Mathematical Studies in the Social Sciences, University of Stanford, Stanford, CA.

Delgado, Porter and Stern, (2011). Clusters, Convergence, and Economic Performance

Khanna, T. and Oberholzer-Gee, F. (2006). The Political Economy of Firm Size

Distributions Evidence from Post-Reform China. Working paper

Malerba, F. and Montobbio, F. (2003). Exploring factors affecting international technological specialization: the role of knowledge flows and the structure of innovative activity. Journal of Econ. Vol.13: 411–434

Jacobs, J. (1969) The Economy of Cities. New York: Vintage Books.

Jaffe, A. B., Trajtenberg, M., Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics, 63: 577–598.

Maggioni, M.A., Uberti, T.E. (2007) Inter-regional knowledge flows in Europe: an econometric analysis. In: Frenken, K. (ed.) Applied Evolutionary Economics and Economic Geography, pp. 230–255. Edward Elgar Publishing, Cheltenham.

Meng, Q.X. and Li, M.Z. (2002). New Economy and ICT development in China. Information Economics and Policy 14, 275–295

Neffke, F. (2009) Productive Places. The Influence of Technological Change and Relatedness on Agglomeration Externalities, PhD thesis, Utrecht University, Utrecht.

Neffke, F. and Henning, M. S. (2008) Revealed relatedness: Mapping industry space. Papers in Evolutionary Economic Geography, Utrecht, University of Utrecht.

Neffke, F., Henning, M. and Boschma, R. (2009). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. Papers in Evolutionary Economic Geography (PEEG) 0916,

Neffke, F., Henning, M. and Boschma, R. (2011). How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions, Economic Geography, vol. 87(3), pages 237-265, 07.

Porter M. E. (1998). Clusters and the new economics of competition. Harvard Business Review 76(6): 77–90.

Ramani Shyama V. and Looze De Marie-Angele (2002). Using patent statistics as knowledge base indicators in the biotechnology sectors: An application to France, Germany and the U.K. Scientometrics. Vol. 54, No. 3

Schmoch U., (2008). Concept of a Technology Classification for Country Comparisons. Final Report to the World Intellectual Property Organization (WIPO)

Stephen B. Tallman and Phene, A. (2007) Leveraging Knowledge across Geographic Boundaries, Organization Science, 18(2): 252-260

Van Zeebroeck, N., Van Pottelsberghe de la Potterie, B., and Han, W. (2006) Issues in measuring the degree of technological specialization with patent data. Scientometrics, Vol. 66, No. 3, pp. 481-492.

Wang Cassandra C. and Lin George C.S. (2008). The Growth and Spatial Distribution of China's ICT Industry: New Geography of Clustering and Innovation Issues & Studies 44, no. 2, 145-192.

William H.A., Johnsona and Qing Liu, (2011) Patenting and the role of technology markets in regional innovation in China: An empirical analysis, The Journal of High Technology Management Research. Vol. 22, Issue 1, 14-25

Zhang, Li and Schoonhoven, (2009) Strategic Management Journal, 30: 163–183.

Zucker, Lynne, Michael Darby and Brewer, M. (1998). "Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises." American Economic Review. Vol. 88, No. 1, 290-306.

4. INTELLECTUAL PROPERTY RIGHTS AND COMPETITION POLICY ON THE DEVELOPMENT OF ENTREPRENEURSHIP ACROSS COUNTRIES

4.1 ABSTRACT

Institutions, as the rules of the game, influence the emergence and development of entrepreneurship in important ways. Most of the existing studies have investigated entrepreneurship within a given institutional environment without considering the variations of institutions in different national contexts. In this paper we study the impact of two economic institutions that are particularly relevant to entrepreneurship — the intellectual property rights (IPRs) and the enforcement of the competition policy, as well as their interaction effects on the development of entrepreneurship especially those dealing with technological innovations. We propose that IPRs is positively associated with entrepreneurial activity and this effect is contingent upon the enforcement level of competition policy. The hypotheses are examined within a framework of pooling a cross-section of 60 countries during the periods between 2002 and 2007. The findings show surprisingly that strengthened IPR protection adversely affects the entry of entrepreneurs adopting new technology and this relationship is attenuated by the increasing enforcement of competition policy.

Keywords: Entrepreneurship, Institutions and IPRs

4.2 INTRODUCTION

Entrepreneurship has long been viewed as an engine that drives economic development, employment creation, and innovation. Institutions as the rules of the game influence the emergence and development of entrepreneurship in important ways (North, 1990; Baumol, 1996). A greater understanding of institutional differences will aid entrepreneurs, researchers, potential investors, and government policy makers trying to revitalize their economies (Busenitz, Gomez, and Spencer, 2000). Scholars have studied how patent rights (Nelson, 1982) and societal norms (Busenitz & Lau, 1996) affect the level of entrepreneurship within an economy. Most of the studies, however, investigate entrepreneurship within a given institutional environment without considering the variations of institutions in different national contexts (Davidsson and Wiklund, 2001). With a few exceptions, several cross-nation empirical studies have discovered that the institutions such as culture (Mueller & Thomas, 1997), intellectual property rights (Autio and Acs, 2010), bankruptcy law (Peng, Yamakawa and Lee, 2009) and economic freedom (Harbi and Anderson, 2010) influence the motivation and cost of entrepreneurship significantly.

Two economic institutions are particularly relevant to the development of entrepreneurship —intellectual property rights (IPRs) and competition policy. IPRs offer inventors temporary monopoly rights over intellectual properties and provide entrepreneurs with incentive to innovate. Therefore, whether a country allows entrepreneurs to appropriate value from their new ideas through IPRs and how well IPRs are protected create significantly different incentives for individuals engaging in the entrepreneurial activity (Hoskisson, Covin, Volberda and Johnson, 2011). Effective competition policy instead lowers entry barriers by preventing monopolization in favor of a competitive market, which increases entrepreneurial opportunities and encourage the entry of the entrepreneurial firms.

The current study aims to address the following research questions. What is the impact of intellectual property protection on the emergence of early-stage entrepreneurs, particularly those dealing with technological innovation activities and to which extent does the enforcement of competition policy affect this relationship? We define in this paper the early-stage entrepreneur as a working age-adult who is either actively trying to start a new entrepreneurial firm, or who is currently acting as the owner-manger of a new entrepreneurial firm. The technology entrepreneur is defined as an individual involved in early-stage entrepreneurial activity that claims to use new technology in the production of goods or services. Technology entrepreneurs are particularly relevant in this context because intellectual property is the key asset possessed by this type of firm and the importance and economic value of this asset is subject to the establishment and enforcement of the IPR regime. We propose that IPR protection is positively associated with entrepreneurial activity and this effect is contingent upon the enforcement level of competition policy. Specifically, stronger IPR protection encourages the entry of technology entrepreneurship. The enforcement of competition policy complement IPRs in that increasing the level of enforcement of competition policy will intensify the positive relationship between IPRs and the technology entrepreneurship.

We test the hypotheses using annual data from the Global Entrepreneurship Monitor during the period of 2002 and 2007 on various measures of entrepreneurship. Data from the World Bank, the Heritage Foundation and the IMD World Competitiveness Yearbook are used to construct the key explanatory and control variables. The findings show surprisingly that instead of encouraging, stronger IPRs adversely affect those entrepreneurs who introduce new technology among other early-stage entrepreneurs. As we expected, IPRs and competition policy complement each other and the negative impact of IPRs on technology entrepreneurs is attenuated by stronger enforcement of competition policy.

We make the following contributions. First, as a cross-nation empirical research, the current study specifically focuses on the variations of institutions such as IPRs and competition policy and examines how different institutions in different national contexts would affect the entrepreneurial activities. Second, we add to the existing studies that mainly look at the entrepreneurs with high growth aspiration by providing the evidence of institutional impact on the entrepreneurs introducing new technologies, which constitute another important group of economic agents contributing substantially to the economic performance of a country. Third and most importantly, we highlight the interaction between two institutions—IPR and competition law. Our findings suggest that institutions work as an ecosystem and they jointly determine entrepreneurial activities in countries. Such interdependence and interaction provide important implications for research and policy makers.

We structure this paper as follows. We begin by reviewing briefly the literature that studies the institutional determinants of entrepreneurial activity with a focus on the link between IPRs and competition policy and the development of entrepreneurship. Then, we develop theoretical arguments leading to the hypotheses. We follow the hypotheses with a discussion of our sample, methods, empirical models, and results. We conclude the paper with implications of our findings and suggestions for future research.

4.3 THEORY AND HYPOTHESES

4.3.1 Entrepreneurship and Institutional Context

Institutions are the rules of the game (North, 1990; Powell and DiMaggio, 1991). They guide the behavior of individuals and facilitate interactions between economic agents through defining the structure for exchange that influences uncertainties and transaction costs, hence the reward or incentive system in the economy and the feasibility and profitability of engaging in certain economic activities (Baumol, 1996; Gagliardi, 2008). The quality of institutions significantly influences the economic outcomes of the individual or organization’s undertakings. Entrepreneurs, as a specific type of economic agent, are affected by their institutional setting. Institutions lay out the foundation for an ecosystem within which opportunities and threats emerge for entrepreneurs.

An emerging group of empirical studies have built upon this theoretical framework and been focusing on the role of institution in determining the development of entrepreneurship. Autio and Acs (2010) claim that strategic entrepreneurial behaviors cannot be fully understood without giving attention to the context in which those behaviors are observed. Applying real options logic, they show that a country's IPR regime affect the effect of an individual's human and financial capital on entrepreneurial growth aspirations. Lee, Yamakawa, Peng and Barney (2010) posit that entrepreneurs and firms strategically respond to the formal institutions of a society and they find that entrepreneur-friendly bankruptcy laws are significantly correlated with the level of entrepreneurship development as measured by the rate of new firm entry. Using national patent and self-employment data, Harbi and Anderson (2010) find that institutional environment influences entrepreneurship and innovations differently−several institutional factors of economic freedom encourage self-employment but discourage innovation.

4.3.2 Intellectual Property Rights and Entrepreneurship

Entrepreneurship involves the discovery, evaluation, and exploitation of opportunities to introduce new goods and services, ways of organizing markets, production processes, and handling materials through efforts that previously had not been exercised (Venkataraman, 1997; Shane and Venkataraman, 2000). Creation and recognition of opportunities is one of the most important prerequisites of entrepreneurial activity. Entrepreneurship takes a wide variety of forms by engaging in various opportunity-discovery and exploitation activities mentioned above and acting as knowledge creators and knowledge users.

Knowledge as a public good is non-rivalrous and non-exhaustible in that the consumption of knowledge by one does not preclude the accessibility of others to the same knowledge. Knowledge can be consumed by many people at once, without reducing the value, quantity or utility and it can also be reproduced with almost marginal cost. However, to produce any kind of knowledge, an economic agent (e.g. individual, firms, and research institutions) has to make investment of various types (e.g. human, financial, technological and organizational resources) and at different levels of intensity, which normally represent a sizable cost of the agent. Without effective mechanisms to exclude others from using their innovations as free riders due to the public goods nature of knowledge, economic agents would have difficulties to recoup the investment. Lack of protection for the intellectual properties lowers their incentive to invest in and develop new knowledge in the first place.

IPRs grant certain time-limited rights to creators so that they can have temporary monopoly over those intellectual properties (WIPO, 2004). IPRs protect the owners of the IP by excluding the rivals from accessing and utilizing their creations without authorization. Increasing the strength of IPR protection therefore provides firms and individuals (including potential entrepreneurs who may or may not engage in the commercialization process) with incentives to invest and produce more new knowledge and subsequently more potential entrepreneurial opportunities. In the meantime, the exclusive right of the IP owner has another option of IPR application in practice, which is the possibility of selling or licensing his right through knowledge market where technology suppliers and user exchange needs with each other. This increases the accessibility to certain knowledge for potential entrepreneurs (knowledge users) who are planning to bring the market new products or services based fully or partially on this knowledge, which they might not be able to access and explore otherwise.

Small businesses and entrepreneurial firms have shown great potential to bring forward innovation and technological changes (Acs and Audretsch, 2005). They are regarded as technology entrepreneurs that are defined in the current study as working-aged individuals who claim to adopt new technology in the production of goods or services while starting or running new firms. Intellectual property is one of the key assets associated with this type of firms and the technological importance and economic significance of this asset is subject to the changes of a country's IPR regime. Strong IPR protection promotes the dedication to new technological knowledge production and diffusion which in turn increase the level of knowledge stock, technological capacity, knowledge transfers and spillovers in the whole economy (Audretsch and Acs, 1994). Overall, this drives the emergence of more technological opportunities and provides potential entrepreneurs with more possibilities to take part in the entrepreneurial activities through exploring these emerging opportunities. Based on the above argument we propose that:

Hypothesis 1 (H1): The strength of IPR protection is positively associated with the probability of an individual engaging in the technology entrepreneurship.

4.4.3 Competition Policy and Entrepreneurship

Competition policy is a set of policies that promote competition in local and national markets, as well as legislations (e.g. competition law), judicial decisions and regulations specifically aimed at preventing anti-competitive business practices and unnecessary government interventions, avoiding concentration and abuse of market power (Dube, 2008). There are basically two ways to look at and study competition policy in the literature: one concerns the existence of certain kinds of laws and regulations whereas the other view focuses on the enforcement of these laws (Nicholson, 2004). An appropriate law and policy in place thus is not sufficient unless it is an effective one, with appropriate guidelines and enforcement power (Rey, 1997). Here we are interested in the actual enforcement the competition policy.

Competition is essential to innovations and entrepreneurship. Competition policy alters the level of competition in the market place and influences the emergence of entrepreneurship in several ways. Through ensuring the availability of multiple suppliers of goods, services and technologies that could effectively compete against each other the effective enforcement of competition policy creates pro-competitive environment wherein larger incumbent firms are prevented from abusing their market powers to exploit smaller competitors and consumers, removes barriers of entry so that new firms could gain their access to the markets and fosters competition in order to boost innovation and accelerate technological progress. These measures, if well enforced, could all provide an entrepreneur-friendly environment wherein potential entrepreneurs could acquire and explore new technological opportunities through establishing new ventures. Therefore, failing to enforce competition policy and provide healthy business environment could harm entrepreneurship since potential entrepreneurs will be placed at a disadvantaged position, where the available opportunities are limited and the hazard of failure are high.

The same principles of competition policy apply to the areas (e.g. licensing agreement of IP, in particular patents, technology transfer and other IP pooling arrangements) in which IPRs may be used to charge excessive prices, prevent access to protected technologies and restrict competition between technologies that are economic substitutes for one another. The enforcement of competition policies therefore complement IPR protection and promote the emergence of technology entrepreneurship. Specifically, at a given level of IPR protection, fair and pro-competitive licensing terms (e.g. compulsory license) under competitive market assured by the strong enforcement of competition regulations increase the access of potential entrepreneurs (knowledge users) to new technologies and encourage the technology adoption on the one hand. Well-functioning competition policy, on the other hand, makes it more difficult for big incumbent firms to acquire new, small and promising firms (e.g. technology ventures). Under this circumstance, potential entrepreneurs could gain more space to explore new opportunity and develop new ventures with limited detrimental impacts from the market power of big dominating firms. Meanwhile, the option of assigning or licensing patent for the knowledge creators under stricter competition regulations could be less profitable than it is under the weak enforcement of competition policy as more bargaining power is shifted to the knowledge users. Therefore, there will be a higher chance that potential entrepreneurs (knowledge creators) will commercialize their ideas through entering the market where there are more opportunities and higher probability they could compete with and even defeat existing established firms. We therefore propose that:

Hypothesis 2 (H2): Enforcement of competition policy moderates the positive relationship between IPRs and technology entrepreneurship such that the stronger the enforcement of competition policy, the stronger this relationship.

4.4 *METHODS*

4.4.1 Data and Sample

We test our hypotheses using annual survey data from the Adult Population Survey (APS) of Global Entrepreneurship Monitor (GEM) on various measures of entrepreneurship from 2002 to 2007. GEM systematically researches entrepreneurial behavior around the world. It defines entrepreneurs as "adults in the process of setting up a business they will (partly) own and / or currently owning and managing an operating young business." Based on the stage, profits and salary payments of the business, the nascent entrepreneur, baby business and established business are regarded as three main classes of the entrepreneurship.

We examine in this study the first two types of entrepreneurship, which together is also called the "early-stage entrepreneur" or the "total entrepreneurial activity" (TEA). TEA is defined as the working adult-age individual (18 - 64) who is either actively trying to start a new entrepreneurial firm, or who is currently acting as owner-manger of a new entrepreneurial firm. Initial database contains 802,318 individuals from 18 to 64 years old in 60 countries. This data is summarized in Table 10, in which we report the total number of observations (i.e. the individuals who have participated in the survey), the early-stage entrepreneur as the share of total participants in each country over the 7 years and the technology entrepreneurs that we are particularly interested in. Technology entrepreneurship is a sub-category of TEA that claims to adopt new technologies in the production of the goods or services. Table 10 presents the scale of technology entrepreneurs as share of the total early-stage entrepreneurs in each country over the observation period. We can tell from this table that the rate of early-stage and technology entrepreneurship varies widely across countries. On average, there are about 6.7% of total observations claiming to be involved in the early-stage entrepreneurial activity, 12.14% of which claim to adopt new technologies.

TABLE 10 COUNTRIES AND ENTREPRENEURSHIP IN THE SAMPLE

Country	Total Obs.	TEA		Tech. Entrepreneurship		Country	Total Obs.	TEA		Tech. Entrepreneurship	
		%	Obs.	%	Obs.			%	Obs.	%	Obs.
United States	25,543	8.87%	2,266	9.75%	221	Singapore	15,880	5.63%	894	13.09%	117
Russia	6,023	3.02%	182	7.14%	13	Thailand	7,043	17.11%	1,205	16.10%	194
South Africa	20,023	4.74%	949	21.07%	200	Japan	11,776	2.40%	283	9.54%	27
Greece	10,008	6.45%	646	27.71%	179	Korea	2,015	13.00%	262	15.27%	40
Netherlands	21,178	3.75%	794	9.07%	72	China	10,835	14.31%	1,550	16.90%	262
Belgium	18,196	3.06%	557	26.75%	149	Turkey	4,817	5.27%	254	5.12%	13
France	11,919	2.94%	350	14.57%	51	India	6,708	11.55%	775	10.32%	80
Spain	96,550	6.28%	6,066	5.06%	307	Canada	14,495	6.83%	990	9.80%	97
Hungary	11,756	4.77%	561	9.27%	52	Uganda	3,040	29.24%	889	13.05%	116
Italy	12,950	3.58%	464	15.09%	70	Portugal	3,023	7.21%	218	12.84%	28
Romania	2,046	2.54%	52	0.00%	0	Ireland	11,993	7.05%	845	9.70%	82
Switzerland	11,608	5.94%	689	12.48%	86	Iceland	12,018	10.90%	1,310	15.88%	208
Austria	4,199	4.29%	180	6.11%	11	Finland	12,030	4.34%	522	11.30%	59
UK	158,083	4.41%	6,967	9.52%	663	Latvia	5,922	5.13%	304	7.57%	23
Denmark	20,037	5.38%	1,077	8.54%	92	Serbia	2,200	6.18%	136	11.76%	16
Sweden	36,731	3.14%	1,153	13.10%	151	Croatia	12,017	4.54%	545	21.10%	115
Norway	12,969	5.96%	773	14.75%	114	Slovenia	15,089	3.97%	599	11.19%	67
Poland	4,001	6.20%	248	10.08%	25	Czech republic	2,001	6.25%	125	37.60%	47
Germany	40,724	4.92%	2,002	12.29%	246	Venezuela	5,794	23.09%	1,338	10.31%	138
Peru	6,004	34.41%	2,066	12.29%	254	Ecuador	2,010	27.06%	544	15.44%	84
Mexico	5,028	6.84%	344	9.59%	33	Uruguay	3,997	9.58%	383	9.92%	38
Argentina	12,039	12.76%	1,536	10.48%	161	Kazakhstan	2,000	9.15%	183	4.92%	9
Brazil	14,000	12.44%	1,741	3.56%	62	Puerto Rico	1,998	2.80%	56	16.07%	9
Chile	12,020	12.36%	1,486	19.58%	291	Hong Kong	8,062	4.11%	331	8.46%	28
Colombia	4,103	21.35%	876	17.58%	154	Jamaica	5,849	19.42%	1,136	19.37%	220
Malaysia	2,005	11.52%	231	9.52%	22	Taiwan	2,236	3.89%	87	28.74%	25
Australia	12,564	8.32%	1,045	11.10%	116	Jordan	2,000	19.00%	380	35.53%	135
Indonesia	2,000	19.30%	386	31.35%	121	United Arab Emirates	4,181	6.60%	276	33.33%	92
Philippines	2,000	21.25%	425	21.41%	91	Israel	5,956	5.64%	336	14.58%	49
New Zealand	6,945	12.41%	862	13.11%	113	Dominican Republic	2,081	16.05%	334	7.78%	26
						Total	**802,318**	**6.74%**	**54,064**	**12.14%**	**6,564**

Data from the World Bank, the Heritage Foundation and the World Competitiveness Report are used to construct the key explanatory and control variables. IPR protection measure comes from the index of property rights from the Economic Freedom database of the Heritage Foundation. The Heritage Foundation has tracked the march of economic freedom in 183 countries around the world with 10 influential Index of Economic Freedom and has been commonly used by many scholars (Acemoglu and Johnson 2005; Aidis, et al. 2007; Autio and Acs, 2010). Effectiveness of competition policy indicator is drawn from the World Competitive Yearbook. This report constructs the indicator based on a survey of business leaders, which were asked to rate, on a scale from 1 (lowest value) to 10 (highest value), whether antimonopoly policy promotes competition. It is one of the most comprehensive indicators available in terms of countries included and time periods covered. It has been used in many studies (e.g. Nicholson, 2004; 2008; Kronthaler, 2007).

4.4.2 Variables and Measures

Dependent variable. *Technology Entrepreneur* is defined as an individual involved in *early-stage entrepreneurial* activity (i.e. an working-age adult who is starting a new business or currently an owner-manager of a new business that has paid salaries, wages, or any other payments to the owners not more than 42 months) that claims to use (will use or is currently using) new technology in the production of the goods or services. A technology is considered new if it was not available more than a year ago. It is coded as a dummy variable and it equals to1 if a person is a technology entrepreneur and takes value 0 otherwise.

Independent variables. *Intellectual Property Rights* is defined as the degree to which a country protects private property rights and the degree to which its government enforces those laws and regulations. The IPR protection variable combines various aspects of the degree to which private property is protected in a given country, intellectual property rights are respected, and citizens are protected against expropriation of their properties (Autio and Acs, 2010). The index scales from 10 (lowest value) to 100 (highest value). The more certain the legal protection of property, the higher a country's score is.

Enforcement of Competition Policy is defined as how business leaders perceive competition law. We use data from the IMD World Competitive Yearbook (WCY). This report constructs the indicator based on the Executive Opinion Survey, which were asked to rate, on a scale from 1 (lowest value) to 10 (highest value), whether competition legislation is efficient in preventing unfair competition. The higher value indicates higher level of enforcement of competition policy and more effectively the policy could promote market competition.

Control variables. We include the following variables that could potentially affect the development of entrepreneurship as controls in the model.

Some of the key socio-demographic features of entrepreneurs are controlled. We control the age of an individual as studies have suggested that middle-aged persons are more likely to start a business (Reyonolds et. al., 1999; Minnittiet et. al., 2005). Entrepreneurial activity is found to vary significantly with gender. Being a male is more likely to drive up the rates of entrepreneurship (Grilo and Thurik, 2005; Estrin and Mickiewicz, 2009). It is coded as a dummy variable and takes value 1 if the individual interviewed is male and 0 otherwise. Research shows that individuals with higher educational attainment are more likely to start a business (Minnitti et al. 2005). Education is coded as a dummy variable takes value 1 if the individual interviewed has a graduate experience and 0 otherwise (i.e. primary, secondary, post secondary). ***Income level*** influences individual's perceived opportunity cost and income expectation positively (Smith and Powell, 1990; Autio and Acs, 2010). Household income is classified into 3 categories: lower 1/3, middle1/3 and higher 1/3. We set dummy variables to each category with lower 1/3 as reference group.

Perceptions, attitudes and skills of entrepreneurs are also taken into account as controls in our analysis. ***Knowledge and*** skills is coded as a dummy variable and takes value 1 if the individual interviewed believes to have the required skills and knowledge to start a business and 0 otherwise. Opportunity perception is coded as a dummy variable and takes value 1 if the individual interviewed sees good opportunities to start a business in the next 6 months and 0 otherwise (Naudé, Amorós and Cristi, 2011). Fear of Failure is coded as a dummy variable and takes value 1 if the individual interviewed indicates that fear of failure would prevent them from setting up a business and 0 otherwise. ***Acquaintance with other entrepreneurs*** is coded as a dummy variable and takes value 1 if the individual interviewed knows other person who started a business in the past 2 years and 0 otherwise. The cultural views or acceptability of entrepreneurship in a particular nation is believed to positively related with the probability of early-stage entrepreneurial activity (Naudé, et.al, 2011). We control ***social support*** and set dummy variable equal to 1 when people believes that starting a business is considered as a good career choice, 0 otherwise.

Based on the World Development Indicators from the World Bank, we also include some macro economic factors proven to be associated with the development of entrepreneurship. Country's growth rate positively associated with the entry of new firms (Kawai and Urata, 2002). Thus, we control for the ***growth rate of GDP*** measured as annual percentage growth rate of GDP at market prices based on constant local currency. It is lagged one year and log transferred. We control for the ***interest rate*** in a given year measured by the lending interest rate adjusted for inflation as measured by the GDP deflator to capture the variance and stability of a country's financing infrastructure (Goderis and Loannidou, 2008). ***Population*** of a country that reflect the size of the market is controlled and measured by counting all residents regardless of legal status or citizenship, except for refugees not permanently settled in the country of asylum. It is suggested that higher levels of unemployment increase the chances of self-employment. Thus we include ***unemployment*** measured as the share of the labor force that is without work but available for and seeking employment as another control. All variables discussed above are log transformed. Finally, we control for **transition economies**[6] which are the countries dealing with transformation from a centrally planned economy to a free market economy (Feige, 1994) because of their idiosyncratic economic history (Autio and Acs, 2010).

4.4.3 Econometric Models

In the Hypothesis 1, we are interested in the impact of IPR protection on individual's decision engaging in the technology entrepreneurship. In the Hypothesis 2, we examine the moderating role of competition policy enforcement in the relationship between IPR protection and individual's decision to be a technology entrepreneur. The dependent variable is binary indicating whether or not the person surveyed is a technology entrepreneur.

We have to tackle here a sample selection issue in the econometric analysis as an individual that will adopt new technology can only be observed for those people who first decided to become an early-stage entrepreneur. This is a self-selection process in which the choice to be an early-stage entrepreneur in the first place might not be random but influenced by some factors that at the same time drive individuals to adopt new technology and become technology entrepreneurs. The two choices discussed above are not independent from each other and not taking the selection into account will bias the estimates (Heckman, 1979). The two-stage Heckman selection model is adopted for handling this sample selection issue.

To facilitate model identification, the selection model and outcome model in two stages should have at least one variable different, meaning that we should include at

---

[6]The following countries in GEM survey are listed as transition economies (the IMF, 2000; the World Bank, 2002; 2009): China, Croatia, Czech Republic, Hungary, Latvia, Poland, Romania, Russia, Slovenia and Serbia.

least one variable in the selection equation (i.e. being a early-stage entrepreneur) that is not associated with the choice of adopting new technology, therefore, can be excluded from the outcome equation (i.e. being a technology entrepreneur). Drawing upon existing literature showing that the increased likelihood of an individual entering entrepreneurship if he belongs to a more entrepreneurial social group as they may enhance their perceptions of entrepreneurs' social status as well as their learning experiences (Nanda and Sorensen, 2010; Giannetti and Simonov, 2009), we decide to include the personal acquaintance of other entrepreneurs as a determinant that is more relevant for an individual's selection to become an early-stage entrepreneur than for his selection of adopting new technology.

4.5 RESULTS

Table 11 and Table 12 present the descriptive statistic such as means, standard deviations and the correlations for all variables included in our models. We check variance inflation factors (VIFs) of the independent variables included in the models. VIF measures how much the variance of an estimated regression coefficient is increased because of collinearity. In the outcome equation, the mean value of VIFs is 1.92 which is less than 6 and the maximum value of VIF is 4.41 which is smaller than 10. In the selection equation the values are 1.65 and 4.27. Overall, this analysis suggests little problem of multicollinearity[7].

---

[7]Rule of thumb: individual VIFs are greater than 10 and the average VIF is greater than 6 are generally seen as indicative of severe multicollinearity.

TABLE 11 DESCRIPTIVE STATISTICS

Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Technology entrepreneur	51529	0.12	0.33	0	1
IPRs	48118	71.44	19.95	28.75	90.00
Competition policy	45917	5.74	1.22	0.00	7.88
Population	48068	111.94	261.90	0.29	1321.29
GDP growth	42655	4.50	3.06	-10.90	14.20
Interest rate	31851	7.07	9.93	-7.80	47.30
Unemployment	41084	7.86	4.28	1.20	30.50
Age	51529	38.02	11.15	18	64
Gender	51519	1.40	0.49	1	2
Education	51529	0.19	0.39	0	1
Income	30298	23515.82	31171.79	33	68100
Knows other entrepreneurs	28451	0.64	0.48	0	1
Opportunity perception	25299	0.59	0.49	0	1
Knowledge and skills	28138	0.86	0.35	0	1
Fear of failure	28201	0.23	0.42	0	1
Social support	20469	0.67	0.47	0	1
Survey year	51529	2004.85	1.70	2002	2007
Transition economy	51529	0.09	0.28	0	1

TABLE 12 CORRELATIONS OF VARIABLES

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 Technology entrepreneur	1.00																		
2 IPRs	-0.06	1.00																	
3 Competition policy	-0.05	0.61	1.00																
4 Population	0.04	-0.51	-0.07	1.00															
5 GDP growth	0.05	-0.52	-0.14	0.16	1.00														
6 Interest rate	-0.19	-0.02	-0.01	-0.17	-0.17	1.00													
7 Unemployment	0.06	-0.28	-0.10	0.01	-0.03	0.27	1.00												
8 Age	-0.02	0.14	0.04	-0.09	-0.11	-0.05	-0.07	1.00											
9 Age (squared)	0.02	-0.10	-0.02	0.08	0.05	0.05	0.06	-0.70	1.00										
10 Gender	0.02	0.00	0.03	0.06	-0.03	-0.03	-0.04	0.06	-0.06	1.00									
11 Education	-0.02	0.14	0.11	-0.07	-0.04	-0.06	-0.09	0.03	-0.06	-0.05	1.00								
12 Income_mid	-0.03	0.07	0.04	0.00	-0.08	-0.06	0.00	0.01	-0.03	0.00	-0.06	1.00							
13 Income_high	0.04	0.04	-0.01	-0.08	0.07	-0.08	-0.07	-0.01	-0.01	-0.14	0.26	-0.53	1.00						
14 Knows other entrepreneurs	-0.03	-0.02	-0.03	-0.03	0.05	-0.07	0.05	-0.07	0.00	-0.11	0.08	-0.01	0.13	1.00					
15 Opportunity perception	0.01	0.01	0.04	-0.07	-0.03	0.03	0.10	-0.04	0.02	-0.02	0.03	0.01	0.01	0.14	1.00				
16 Knowledge and skills	-0.02	0.05	0.00	-0.09	-0.08	0.03	0.13	0.03	-0.06	-0.10	0.05	0.01	0.06	0.14	0.20	1.00			
17 Fear of failure	0.00	-0.01	-0.04	0.02	0.02	-0.01	-0.11	0.07	-0.07	0.11	-0.07	-0.02	-0.06	-0.05	-0.07	-0.16	1.00		
18 Culture	0.03	-0.14	-0.04	0.16	0.08	0.00	-0.07	-0.01	0.01	0.03	-0.09	-0.04	-0.04	0.00	0.07	0.01	0.04	1.00	
19 Transition economy	0.03	-0.53	-0.48	0.14	0.42	-0.23	0.06	-0.07	0.04	-0.09	-0.04	-0.04	0.11	0.12	-0.08	-0.02	-0.04	-0.04	1.00

The results of estimating the impact of IPRs on the probability of an individual engaging in the technology entrepreneurship (H1) and the moderating role of competition policy (H2) using the Heckman selection models are presented in Table 13. The first stage is the selection model predicting the probability of an individual engaging in early-stage entrepreneurial activity. The second stage then estimate the independent effects of the explanatory and control variables on the probability of an individual to become a technology entrepreneur. Model 1 is the baseline model containing only the control variables. Model 2 estimates the main effects IPRs and competition policy on technology entrepreneurship. Model 3 is the full model containing the key independent variables, their interaction term and all control variables.

First of all, the inverse Mill's ratio in Table 13 shows statistically significant influences in all models. This result indicates that our decision to adopt the Heckman selection procedure is justified. Surprisingly, the effect of IPR protection exhibits negative (-0.17) and significant effect at the level of 0.05, indicating that a higher level of IPR protection is negatively associated with the probability of an individual engaging in the technology entrepreneurship. Hypothesis 1 is not supported therefore. The results show as well that the enforcement of competition policy exhibits positive (1.57) and significant effect at the level of 0.001 on the relationship between IPR and technology entrepreneurship. In other words, IPR protection and the enforcement of competition policy complement each other, which provides full support for Hypothesis 2.

Due to the selection procedure, we should calculate the conditional marginal effects for all estimated results. Conditional marginal effect is the marginal effect of an independent variable on the dependent variable conditional on selection and consists of two components. First, there is the direct effect of the independent variable, which is captured by the coefficient in the outcome model. Second, there is an indirect effect if the independent variable also appears in the selection equation. This is because a change in a given variable not only changes the predicted value of the dependent variable, but also the probability that an observation is actually in the sample. Thus, the marginal effect of IPR on the predicted probability of technology entrepreneurship is -0.04. It indicates that holding all other variables constant at their means, one unite increase in the IPR protection leads to the decrease of the probability of an individual engaging in the technology entrepreneurship by 4%. While everything else being equal, one unite increase in both IPR and the enforcement level of competition policy will increase the probability of an individual engaging in the technology entrepreneurship by 38%.

TABLE 13 RESULTS OF REGRESSION ANALYSIS PREDICTING TECHNOLOGY ENTREPRENEURSHIP

	Model 1		Model 2		Model 3	
Outcome Model (Technology Entrepreneurship)	Coefficient	Conditional marginal eff.	Coefficient	Conditional marginal eff.	Coefficient	Conditional marginal eff.
Inverse Mill's ratio	-0.35**	-0.08*	-0.38***	-0.09***	-0.72***	-0.17***
IPR			-0.17*	-0.04*	-0.37**	-0.09**
Competition law	-0.28**	-0.07**	-0.16 †	-0.04 †	0.93***	0.22***
IPR x Competition law					1.57***	0.38***
Age [a]	-0.16	-0.04	-0.15	-0.04	-0.31*	-0.08*
Age (squared)	-0.25	-0.06	-0.27	-0.07	-0.63*	-0.15*
Gender (female)	0.04	0.01	0.04	0.01	0.02	0.01
Education (graduate exp.) [a]	-0.04	-0.01	-0.03	-0.01	-0.05	-0.01
Income_middle1/3 [a]	-0.03	-0.01	-0.02	0	0	0
Income_upper1/3 [a]	0.13†	0.03†	0.15*	0.04*	0.2**	0.05**
Knowledge and skills [a]	-0.06	-0.01	-0.05	-0.01	-0.05	-0.01
Opportunity perception [a]	0.07	0.02	0.07	0.02	0.07	0.02
Fear of failure [a]	-0.08	-0.02	-0.08	-0.02	-0.11†	-0.03†
GDP growth	0.3***	0.07***	0.24**	0.06**	0.26**	0.06**
year_2003 [a]	0.53	0.13	0.44	0.11	-0.07	-0.02
year_2004 [a]	0.33	0.08	0.29	0.07	0.04	0.01
year_2005 [a]	0.31***	0.08***	0.34***	0.08***	0.36***	0.09***
year_2006 [a]	0.29***	0.07***	0.29***	0.07***	0.29***	0.07***
Transition Economy [a]	-0.15†	-0.04†	-0.18*	-0.04*	-0.28**	-0.07**
_cons	-2.22***		-2.19***		-2.75***	
Selection Model (Early-stage Entrepreneurship)						
IPR	0.27***		0.27***		0.27***	
Competition law	0.75***		0.75***		0.75***	
IPR x Competition law	1.51***		1.51***		1.51***	
Population	0.07***		0.07***		0.07***	
GDP growth	0.36***		0.36***		0.36***	
Interest rate	0.12***		0.12***		0.12***	
Unemployment	0.11***		0.11***		0.11***	
Age	-0.45***		-0.45***		-0.45***	
Age (squared)	-1.17***		-1.17***		-1.17***	
Gender (female)	-0.09***		-0.09***		-0.09***	
Education (graduate exp.)	0.07*		0.07*		0.07*	
Income_middle1/3	0.03		0.03		0.03	
Income_upper1/3	0.12***		0.12***		0.12***	
Knows other entrepreneurs	0.4***		0.4***		0.4***	
Fear of failure	-0.19***		-0.19***		-0.19***	
Social support	0.19***		0.19***		0.19***	
Year_2003	-1.4***		-1.4***		-1.4***	
Year_2004	-0.93***		-0.93***		-0.93***	
Year_2005	0.06*		0.06*		0.06*	
Year_2006	-0.04		-0.04		-0.04	
Transition economy	-0.31***		-0.31***		-0.31***	
_cons	-2.31***		-2.31***		-2.31***	
Wald chi2	66.75***		68.26***		85.83***	
NO. of obs.	25879		25879		25879	
Log pseudolikelihood	-1630.33		-1628.91		-10225.24	
Pseudo R2	0.02		0.02		0.03	

(a) Marginal effect for discrete change of dummy variable from 0 to 1.

*** p< 0.001, ** p<0.01, * p<0.05, † p<0.1

4.6 DISCUSSION

We investigate in this study the relationship between IPRs and the development of technology entrepreneurship and the extent to which this relationship is moderated by the enforcement of competition policy across different countries.

The final results show that instead of stimulating, higher levels of IPR protection hamper the entry of entrepreneurs that adopt new technologies. This result is unexpected and the explanation could be the following. On the one hand, the inventor of patented knowledge is given a statutory right to prevent others from commercially exploiting their invention, which is frequently referred to as a monopolistic right to exclude others from making, using or selling the invention (WIPO, 2004). This gives the inventor the sole ability to commercialize their patented knowledge and recoup the costs of the innovation. On the other hand, the right to license others to exploit the invention is an important additional source of income to the inventor and sometimes can be the only source when the owner of the property right is not well situated to engage in large scale commercial exploitations (OECD, 1989).

Under stronger IPRs protection, potential entrepreneurs as patent owners (knowledge creators) are more likely to opt out from being entrepreneurs because they are usually better off to license out the patent than to commercialize it by them. This is partly due to the preferential licensing terms in favor of inventors under stronger IPR protection. Meanwhile, lacking relevant experience in downstream markets and the substantial cost of establishing complementary assets also lower their inventive of entry. There are potential entrepreneurs that are patent adopters (knowledge users). They acquire and rely on new knowledge produced by others. Under stronger IPR protection, a considerable amount of cutting-edge discoveries has been patented. Access to similar knowledge by potential technology users thus becomes limited (Choi and Phan, 2006) due to various kinds of holdup in negotiating licensing terms often with multiple innovators and producers (e.g. refusal to license, exclusive license, expensive license fee, risk of infringement). This is especially so for those early-stage technology entrepreneurs (potential users of the technology in question) as they are more financially constrained and lack well-developed patent portfolio that could influence the bargaining power in the negotiation processes. Therefore, the entry of technology entrepreneurial firms is deterred. Moreover, innovations are often cumulative and complementary. By granting temporary monopoly right to the access of certain innovations, IPRs raise barriers for subsequent technological advancements that need to be built upon existing knowledge. This will slow down the pace and reduce the total amount of technology discoveries and entrepreneurial opportunities.

The selection model in the Heckman two-stage analysis indicates that IPRs shows positive effect on the total early-stage entrepreneurship while holding the enforcement level of competition policy at it mean value. To better understand the impact of IPRs on the entrepreneurship, we carry out ex-post ad hoc analysis on the relationship between IPRs and total early-stage entrepreneurship. The estimated results are presented in Table 14. Model 4 is the baseline model containing only control variables. Model 5 includes the main explanatory variables. Model 6 is the full model. The results show that IPRs and competition policy have the same complementary effect on total early-stage entrepreneurship as they do on the technology entrepreneurship. It's important to know that the main effect of IPRs on total early-stage entrepreneurship is positive (0.43) and significant at 0.001 level as opposed to the negative effect IPRs have on the technology entrepreneurship. Based on the above analysis, we understand that the effect of IPRs on the entrepreneurial activity clearly varies across different types of entrepreneurship. IPR protection is conducive to the overall entrepreneurs but adversely affects the entrepreneurs adopting new technologies.

TABLE 14. RESULTS OF REGRESSION ANALYSIS PREDICTING TOTAL EARLY-STAGE ENTREPRENEURSHIP

Total early-stage Entrepreneurship	Model 4	Model 5	Model 6
IPR		0.43***	0.27***
Competition law	-0.09†	-0.45***	0.75***
IPR x Competition law			1.51***
Population	0.03***	0.07***	0.07***
GDP growth	0.29***	0.43***	0.36***
Interest rate	0.08***	0.1***	0.12***
Unemployment	0.16***	0.2***	0.11***
Age	-0.39***	-0.43***	-0.45***
Age (squared)	-1.16***	-1.16***	-1.17***
Gender (female)	-0.1***	-0.11***	-0.09***
Education (graduate exp.)	0.11***	0.12***	0.07*
Income_middle1/3	0.03	0.02	0.03
Income_upper1/3	0.13***	0.11***	0.12***
Knows other entrepreneurs	0.41***	0.42***	0.4***
Fear of failure	-0.19***	-0.2***	-0.19***
Social support	0.19***	0.18***	0.19***
Year_2003	-1.43***	-1.36***	-1.4***
Year_2004	-0.93***	-0.94***	-0.93***
Year_2005	0.09***	0.05†	0.06*
Year_2006	0.00	-0.08**	-0.04
Transition economy	-0.41***	-0.36***	-0.31***
_cons	-2.07***	-2.49***	-2.31***
NO. of obs.	27548	25879	25879
Wald chi2	1988.26***	1951.28***	2032.3***
Log pseudolikelihood	-11326.919	-10283.423	-10225.243
Pseudo R2	0.091	0.098	0.103

*** p< 0.001, ** p<0.01, * p<0.05, † p<0.1

We also show the evidence that the interaction of enforcement of competition policy and IPR protection is positively related to the probability of an individual engaging in technology entrepreneurship. This could be understood by the fact that increasing IPR protection can be detrimental to the emergence of entrepreneurial firms adopting new technologies as we just discussed and effective enforcement of competition policy designed to prevent the undue exploitation of market power caused by IPR-related monopoly clearly plays a substantial role in alleviating the negative effect of IPRs on technology entrepreneurship.

Although we did not hypothesize, the enforcement of competition policy has negative effect on the technology entrepreneurship. The possible explanation for this relationship may have something to do with the very specific nature of this particular type of entrepreneurship, which determines that they will not be in favor of very competitive environment. For instance, Casson (2003) argues that entrepreneurship involves the exploitation of a unique opportunity: "*if two or more entrepreneurs compete to exploit the same opportunity, then normally neither of them will obtain any reward*." Entrepreneurship with propensity to innovate is more likely to be motivated by the potential profit generated from commercialization of the innovation, the so called "temporary monopoly profit" that depends on the competitive landscape of the new market (Binks and Vale, 1990). If a potential entrepreneur has tremendous difficulties in charging premium over the new products in which he has invested a lot, as faced in a competitive and dynamic market regulated effectively by pro-competitive policies, he would reasonably choose not to enter and compete in the market. Fazio (2010) discusses about "leapfrog innovation entrepreneurship" which are start-ups involving with "Schumpeterian creative destruction", introducing completely new products and creating new markets. He provides the evidence that this type of entrepreneurship exist in markets characterized by low levels of competition. This seems also in line with the argument made by Chandler (1990), Fligstein (1996) and Choi and Phan (2006) asserting that less aggressive procompetition policy encourages monopolistic rents that attract new entrants by diminishing direct competition and stabilizing industries.

4.7 CONCLUSIONS AND IMPLICATIONS

Drawing upon economics and entrepreneurship literature, we studied in this paper the impact of intellectual property rights, enforcement of the competition policy and their interaction on the development of entrepreneurial initiatives, especially those dealing with innovation activities.

We argue that entrepreneurships are heterogeneous in terms of their motivations and behaviors. Some are interested in growing bigger and faster, some prefer stay small and just make a living out of their businesses, some are after new technologies and overseas market, so on and so forth. But they have at least one trait in common: recognizing and exploring the opportunities emerging from the economy. Opportunities with different natures have different influence on different types of entrepreneurship. IPRs, patent rights specifically, are closely related to the entrepreneurs seeking for technological opportunities. We have shown that stronger protection discouraged individuals to pursue new ventures that explore technological innovations. This is largely due to the fact that development and commercialization of technological invention is generally risky and costly and entrepreneurs are more often than not financially constrained especially at the very early-stage. Strengthening IPR protection thus the related patent protection for technological inventions generates two effects on entrepreneurs adopting new technologies. First, it gives more incentive to potential entrepreneurs (knowledge generators) generate more innovation and make it more profitable for them to license or sell the technology than to commercialize it by themselves though entering the market due to the preferential licensing terms and lack of complementary asset. Second, strong IPR protection makes it more difficult for potential entrepreneurs (knowledge users) to access new technologies due to the temporary exclusive control over IP and abusive licensing terms. Overall, the net effect of IPRs on technology entrepreneurship is negative.

We also investigated the moderating role of competition policy in the relationship between the IPRs and technology entrepreneurship. The results from this study have shown clearly these two institutions complement with each other. In a nutshell, we should not over-simplify the relationship between IPRs and competition policy. IP legislations cannot be designed and implemented in isolation from other legal disciplines, particularly competition policy. Both competition and patent policies can foster innovation, but each requires a proper balance with the other to do so. How one policy's rules are interpreted and applied can affect the other policy's effectiveness (Federal Trade Commission, 2003).

Implications of this study are twofold. First, we show that policies such as intellectual property rights and competition laws have a major impact on entrepreneurship across different national contexts. The appropriate formulation and implementation of these policies can either facilitate or impede the development of entrepreneurs, particularly those in our study aiming to innovate. Policies become an important contextual factor in the emergence of entrepreneurship. Second and more importantly, we show that there is a significant interaction between intellectual property rights protection and competition policy. Economic policies, in order to create a nurturing environment for entrepreneurship, have to be considered as an ecosystem. The interactions and complementarities among constituent policies therefore jointly determine the future health of entrepreneurship.

There are limitations in this study. The measure of IPRs taken from the Heritage Foundation is not clear-cut. It captures the national protection of properties in general, of which intellectual property is an important part. Further researches could use other measures of IPRs such as the one from the World Competitive Report or the Trade Related Intellectual Property Rights (Hamdan–Livramento, 2009). Further studies could draw the distinction of different types of IPRs and investigate the finegrained relationship between IPR protection and entry of various forms of entrepreneurial activity. It is also interesting to compare the differential effects of IPRs, competition policy and their interaction on the De Novo firms and the De Alio firms that are involved in innovative activities and clearly equipped with different level of resource endowment.

4.8 REFERENCES

Aidis, R., S. Estrin and T. Mickiewicz (2009) Entrepreneurial Entry: Which Institutions. Matter? Discussion Paper 7278, London: CEPR.

Audretsch, D. B and Acs, Z. J, (1994). New-Firm Startups, Technology, and Macroeconomic Fluctuations. Small Business Economics, Vol. 6(6), 439-49.

Acs, Z. and D. Audretsch, eds. Handbook of Entrepreneurship Research. Boston: Springer, 2005.

Autio, E. and Acs, Z., (2010). Intellectual property protection and the formation of entrepreneurial growth aspirations (forthcoming), Strategic Entrepreneurship Journal Vol. 4, 234-251.

Baumol, W.J., (1996). Entrepreneurship: productive, unproductive, and destructive. Journal of Business Venturing Vol.11, 3–22.

Binks, M. and Vale, P., (1990), Entrepreneurship and Economic Change, McGraw-Hill Book Company

Burke, A. and Fraser, S. (2005). The Impact of Intellectual Property Rights on Self-Employed Entrepreneurship: an International Analysis. Papers on Entrepreneurship, Growth and Public Policy 2005-13, Max Planck Institute of Economics, Entrepreneurship, Growth and Public Policy Group

Busenitz, L. W., and Lau. C. M. (1996). A cross-cultural cognitive model of new venture creation. Entrepreneurship Theory and Practice, 20(4): 25-39.

Busenitz, L., Gomez, C. and Spencer, J.W., (2000). Country institutional profiles: unlocking entrepreneurial phenomena. Academy of Management Journal 43 (5), 994–1003.

Casson, M., 2003, The Entrepreneur: an Economic Theory, Edward Elgar Publishing.

Cornelius Dube, (2008) Intellectual Property Rights And Competition Policy. Viewpoint.

Choi, Y. and Phan, P. (2006). The Influences of Economic and Technology Policy on the Dynamics of New Firm Formation, Small Business Economics. Vol. 26(5), 493-503,

Davidsson, P. &Wiklund, J. (2001). Levels of analysis in entrepreneurship research: Current research practices and suggestions for the future. Entrepreneurship Theory and Practice, 25, 81-99

Encaoua, D. and Hollander, A. (2002). Competition Policy and Innovation, Oxford Review of Economic Policy, vol. 18, NO. 1.

Federal Trade Commission (2003). To Promote Innovation: The Proper Balance of Competition and Patent Law and patent law and policy.

Feige, Edgar L. (1994). "The Transition to a Market Economy in Russia: Property Rights, Mass Privatization and Stabilization". Alexander, G. and Skapska, G. (eds.), A Fourth Way? Privatization, Property and the Emergence of New Market Economies. London: Routledge.

Gagliardi, F, (2008). Institutions and economic change: a critical survey of the new institutional approaches and empirical evidence. The Journal of Socio- Economics 37, 416–443.

Goderis, B., Loannidou, V.P. (2008). Do high interest rates defend currencies during speculative attacks? New evidence. Journal of International Economics 74 (1), 158–169.

Gian Fazio (2010). Competition and Entrepreneurship as Engines of Growth.

Harbi, E. S. and Anderson R. A., (2010). Institutions and the shaping of different forms of entrepreneurship. The Journal of Socio-Economics Vol. 39, 436–444.

Hoskisson, R. E., Covin, J., Volberda, H. W. and Johnson, R. A. (2011), Revitalizing Entrepreneurship: The Search for New Research Opportunities. Journal of Management Studies, Special Issue: Revitalizing Entrepreneurship Vol. 48(6), 1141-1168.

Intan M. Hamdan–Livramento (2009). Examining How TRIPS Implementation Affects Access to Foreign Technologies for Developing Countries.

Katz, M. and C. Shapiro (1999). Antitrust in Software Markets, in J.A. Eisenach and T.M. Lenard (eds), Competition, Innovation and the Microsoft monopoly: antitrust in the Digital Marketplace, The Progress and Freedom Foundation, Boston, MA, Kluwer

Kawai, H., Urata, S., (2002). Entry of small and medium enterprises and economic dynamism in Japan. Small Business Economics 18, 41–51.

Lee Seung-Hyun, Yamakawa Yasuhiro, Peng Mike W., Barney Jay B. (2010). How do bankruptcy laws affect entrepreneurship development around the world? Journal of Business Venturing.

Lowell W. Busenitz, Carolina Gómez, Jennifer W. Spencer (2000). The Academy of Management Journal, Vol. 43, No. 5, pp. 994-1003

Mattias Ganslandt. (2008). Intellectual Property Rights and Competition Policy. IFN Working Paper No. 726,

Mueller. S. L. and Thomas, A. S. (1997). National culture and entrepreneurial orientation: A nine-country study. Paper presented at the annual meeting of the Academy of Management. Boston.

Naudé W., Amorós E. J. and Cristi, O. (2011). Surfeiting, The Appetite May Sicken:

Entrepreneurship and the Happiness of Nations. Working Paper No. 2011/07

Nelson. R. R., (1982). Government and technical progress: A cross-industry analysis. New York: Pergamon.

Nicholson, M., (2004). Quantifying Antitrust Regimes. Federal Trade Commission Working Paper No. 267.

North, D., (1990). Institutions Institutional Change and Economic Performance. Cambridge University Press, Cambridge.

North, D.C. (1981). Structure and Change in Economic History. New York: Norton and Co.

Pedro Dal Bó, Andrew Foster and Louis Putterman, (2008). Institutions and Behavior: Experimental Evidence on the Effects of Democracy. NBER Working Paper Series No.13999.

Peng, M.W., Yamakawa, Y., Lee, S.H., (2010). Bankruptcy laws and entrepreneur-friendliness. Entrepreneurship Theory and Practice, Vol. 34 (3), 517–530.

Powell, Walter W. and Paul J. DiMaggio. 1991. The New Institutionalism in organizational Analysis. Chicago: University of Chicago Press.

Rey, P., (1997), Competition Policy and Economic Development, mimeo.

Shane, S., (1996). Explaining variation in rates of entrepreneurship in the United States: 1899–1988. Journal of Management 22, 747–781.

Shepherd, D., (2003). Learning from business failure: propositions of grief recovery for the self-employed. Academy of Management Review 28 (2), 318–328.

Smith HL, Powell B. (1990). Great expectations: variations in income expectations among college seniors. Sociology of Education 63(3): 194-207.

Venkataraman, S., (1997). The distinctive domain of entrepreneurship research: an editor’s perspective. In: Katz, J., Brockhaus, R., (Eds.). Advances in Entrepreneurship, Firm Emergence and Growth, vol. 3. JAI Press, Greenwich, pp. 119–138.

Wagner, J. (2007). What a Difference a Y makes – Female and Male Nascent Entrepreneurs in Germany. Small Business Economics, 28(1), 1-21.

Westhead, P., Ucbasaran, D. and Wright, M. (2005). Experience and Cognition: Do Novice, Serial and Portfolio Entrepreneurs Differ? International Small Business Journal 23(1), 72-98.

WIPO Intellectual Property Handbook: Policy, Law and Use. (2004). WIPO Publication NO. 489 (E).

Shane, S., Venkataraman, S., (2000). The promise of entrepreneurship as a field of research. Academy of Management Review 26, 13–17.

Competition Policy And Intellectual Property Right. (1989). OECD.

5. CONCLUSIONS

In the first study, I investigated the localized knowledge spillover in an industrial cluster and the implications for start-ups innovation. I showed that innovative start-up produced more technological innovations if firm's entry technology was characterized by a higher level of knowledge centrality in the local knowledge base. Over time innovative start-ups demonstrated different propensities of technological diversification in their innovation activities. Knowledge stock and centrality of firm's entry technology in the local knowledge base showed on average negative effect on the probability of technological diversification. Innovative start-ups were more likely to diversify into other technological fields when both the knowledge stock and centrality retains a higher level. To understand the driving forces behind the superior performance of innovative start-ups located in a cluster we have to distinguish what resources have been agglomerated in the cluster, in which way they are agglomerated and which types of firms could benefit most from this agglomeration. The agglomerated resources do not benefit firms in a cluster equally. Innovative start-ups with a certain type of entry technology demonstrate better innovation performance than other firms in the same cluster. Even though entering a high-tech industry cluster, innovative start-ups should carefully choose the entry technologies upon which to build their business through evaluating the characteristics of local knowledge base in order to access, absorb and fully utilize the localized knowledge spillover.

The second study explores the influence of the knowledge centrality of a technology in the knowledge base of industrial clusters in both the focal and other regions on the development of the focal region's technology specialization by taking into account inter-regional effects and the moderating role of the regional technology markets. I argue that there exist two different mechanisms of knowledge flow, unintended knowledge spillovers and intended knowledge transfer. From the viewpoint of the focal region, both the knowledge centrality of a given technology in the knowledge base of the focal and other region have influences on the focal region's technology specialization, but through different mechanisms. Results have shown that, focal region's knowledge centrality of a given technology has negative impact on RTS due to the prevalence of localized knowledge spillovers. Instead, other regions' knowledge centrality influences focal RTS negatively as soon as the effect of technology market is taken into consideration. The results indicate that the effect of intended knowledge transfer on focal RTS highly depends on the development level of technology market in the other ICT clusters, which is a channel promoting the technology trade across regions.

The third study focus on the impact of intellectual property rights, enforcement of the competition policy and their interaction on the development of entrepreneurship and their innovation activities. We argue that entrepreneurships are heterogeneous in terms of their motivations and behaviors. Opportunities with different natures thus have different influence on different types of entrepreneurship. In this regard, the findings from this study demonstrated that stronger IPRs in general encouraged individuals to engage in entrepreneurial activity due to the increasing level of knowledge, capability stock and knowledge spillovers within an economy. While stronger protection discouraged individuals to pursue new ventures that explore technological innovations, which was largely due to the statutory exclusion of others from making, using or selling the invention by the patent holders, which raised the entry barrier substantially for potential technology entrepreneurs. We also find competition policy and IPRs complement with each other in driving the development of entrepreneurship. Implications of this study are twofold. First, we show that policies such as intellectual property rights and competition laws have a major impact on entrepreneurship across different national contexts. The appropriate formulation and implementation of these policies can either facilitate or impede the development of entrepreneurs, particularly those in our study aiming to innovate. Policies become an important contextual factor in the emergence of entrepreneurship. Second and more importantly, we show that there is a significant interaction between intellectual property rights protection and competition policy. Economic policies, in order to create a nurturing environment for entrepreneurship, have to be considered as an ecosystem. The interactions and complementarities among constituent policies therefore jointly determine the future health of entrepreneurship.