The internationalization of industry supply chains and the location of innovation activities

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ABSTRACT

Current policy discussions on offshoring mostly focus on its impact on lower skilled manufacturing and services jobs, assuming that higher-value-added jobs and, especially, innovation activities are not affected by offshoring. Contrary to this view, we suggest that innovation activity will also move abroad as a result of offshoring. Yet, the movement of innovation activities abroad will be conditioned by the nature of knowledge, causing some innovation activities to remain in the US while driving other activities away. To explore this idea we analyze the quantity of and knowledge utilized by innovation activities over time in rare-earth catalyst and magnet technologies, showing how knowledge spillovers among different segments of an industry value chain can play a role in the movement of innovation outside the US. We then develop an innovation model to gain further insight into the characteristics of innovation activities that remain in the US.

Keywords:

Internationalization, rare earth elements, innovation, knowledge spillovers, offshoring

1 INTRODUCTION

After a high-grade deposit was found in California in the early 1950s, the US quickly became a dominant producer of rare earth elements (atomic numbers 21, 39, 57-71). This lead to US developments in large-scale separation techniques for these elements and, subsequently, to significant investment in researching potential uses for the elements. This resulted in the development of important and diverse technology based applications throughout the 1970s and 1980s, including ceramics, catalysts, magnets and phosphors. However, over the past 20 years, the supply chains of rare earth based applications have been offshored from the US to Asia. Today over 85% of rare earth materials originates in China.

Most research to date on vertical specialization, internationalization, and offshoring suggests this industry evolution should not negatively impact the ability and involvement of the US in innovation activities. The global supply and production networks should result in lower costs for individual firms, leading to expanded markets, lower prices for consumers, increased resources for R&D activities and the creation of new business opportunities for existing and new firms (Aron and Singh, 2005, Farrell, 2005, Branstetter, 2006). Other researchers also suggest that similar benefits for firms and national economies arise as firms access local knowledge and learn about complementary technologies not readily accessible at home locations (Dunning, 1995, Florida, 1997, Zander, 2002).

However, many industry representatives have voiced concerns with the ability of the US to maintain leadership in rare earth technology based applications. In fact, US patenting activity in rare earth based technologies has been declining since 1990, the date when most of the manufacturing shifted to Asia (Fifarek et al., 2007). Yet, this trend is not uniform. For example,

the US has continued to be a strong leader in innovation in catalyst applications of rare earths, while innovation in rare earth magnet technology applications has moved away from the US.

These initial findings may call into question our understanding of the impacts of internationalization and offshoring in a region and the common policy approaches to address these trends. Researchers, corporate executives and policy makers typically assert that offshoring benefits national home economies as long as displaced workers are absorbed into other positions where they will be able to generate greater value to the economy (Feenstra, 1998, Jaffee, 2004). Therefore policies typically focus on moving firms and individual workers hurt by internationalization into more value added activities by providing generous severance packages, job-retraining programs and continuing-education grants to upgrade worker skills. The notion behind these programs is that a nation whose jobs are being displaced by offshoring ought to specialize in higher-value-added work, which combined with productivity gains from offshoring, leads to the improvement of a nation's welfare. Innovation activities in particular are those thought to be further away from being affected by offshoring and, in fact, considered to be a desired goal in terms of alternative occupations to those being displaced.

Yet, industry evolution and observed geographic relocation of R&D in the rare earths industry away from the US suggests there is a more important question not currently being properly addressed: *Under what conditions can technology sectors offshore low-skill supply chain operations such as raw material production or manufacturing, while effectively maintaining higher-skill R&D business functions in the home region?*

Although international supply chains, including offshoring, are associated with the development of firm-level capabilities to coordinate geographically dispersed networks of tasks and production activities (Levy, 2005), many higher-value-added innovation activities depend on

complex interactions among different value chain segments that require face-to-face contact (Leamer and Storper, 2005). These critical interactions can be disrupted by geographic distances between business units. As a result, it is possible that, as manufacturing and service positions move overseas, these interactions are jeopardized, leading business managers to relocate engineering work and R&D so that it can be more geographically aligned with production and thus away from the home environment. This is consistent with a looming concern voiced by some academics and the greater public that innovation will also be offshored, ultimately affecting the ability of home economies to maintain their economic growth and leadership (Horvit, 2004, Hira and Hira, 2005). Thus, answering the question above entails a critical understanding of the conditions under which R&D activities are likely to follow the relocation of production and service positions or, on the contrary, they are independent of the location of other segments of the value chain.

This paper explores the changing nature of knowledge used for innovation activities following the internationalization of supply chain activities aiming in particular to understand the drivers that keep innovation activities in the home region, despite supply chain internationalization. To address this issue, the research uses two technology sectors that are part of the rare earth industry, catalysts and magnets, to identify critical factors that influence the location of innovation activities following the offshoring of low technology operations in the rare earth industry supply chain. The analysis draws from firm-level unstructured interviews that identify critical drivers, inputs, and interactions in the innovation processes of these technologies. It also uses detailed information from a subset of over 75,000 patent applications over the period from 1975-2002 that document the generation and regional location of technical knowledge in rare earth elements and their applications. The data is used to examine the

geographic location of innovation activities and the changing nature of knowledge utilized by these activities in different locations.

Results suggest that, as expected, knowledge exchange among different actors in industrial supply chains influence the location of innovation activities. Yet, they also show that demand and the policy environment play a critical role in this process. Innovation in catalyst technologies is highly driven by national and direct customer environmental policy and strategy, which has enabled a strong continued leadership of the US in innovation activities. Magnet technology relies on significantly on supplier, producer and customer interactions and associated knowledge spillovers, contributing to movement of innovation away from the US.

The conclusions of this paper reflect the need to reframe the discussion on appropriate responses to internationalization and offshoring. The policy discussion needs to shift from focusing on moving up the value added chain of activities to critically understand what characteristics and comparative advantages within regions drive innovation activities to remain localized despite the emergence of international supply chains. In the future, if we hope to maintain a healthy rate of innovation in the US, it will be critical for policies to help move firms and workers into activities where the interactions between local business, institutions, and the technology environment matters.

The paper is organized as follows. First, we discuss the background of the rare earth industry, the technology applications of rare earth materials, the internationalization of the rare earth supply chain, and innovation trends within rare earth technologies. We then develop the theoretical background of innovation activities and the internationalization of supply chains. In the subsequent section, we introduce our patent data and regression analyses. We then present the results and discuss their implications. Next we develop an innovation model to gain further

insight into the changing nature of knowledge utilized for innovation activities in different technologies and locations. Finally, we draw conclusions from this analysis and suggest future work.

2 BACKGROUND OF RARE EARTHS

2.1 Production and supply chain of rare earth raw materials

The rare earth elements are a relatively abundant naturally occurring group of fifteen elements. Rare earths exhibit very similar chemical and physical characteristics, varying only slightly in their electronic configurations and ionic radii. Consequently, they were originally very difficult and costly to separate. Prior to 1950, rare earths were not commercially produced in significant quantities and mostly sold as naturally occurring mixtures of the individual elements, such as mischmetal. In the early 1950s, the US quickly became a dominant producer of rare earth raw materials after a high-grade bastnaesite deposit was found in Mountain Pass, CA. Early development was supported largely by the sudden demand for the rare earth element, Europium, created by the commercialization of color television.

By 1965, the single deposit in Mountain Pass had become the most significant source of raw and processed rare earths in the world with reserves of 13 million metric tons. Other significant raw material sources included monazite extracted from Australia, India and Brazil but large scale separation and processing operations remained limited to the US and France. For example, the French firm Rhone-Poulenc (now Rhodia Rare Earths) purchased raw materials mostly from Australia and operated separation facilities in France and the US. The rare earth industry is unique in that there are only a few rare earths processors but the markets for their products are characterized by very large number of diverse, technologically advanced and mostly

small consumers. Molycorp, Inc. of the US is the only fully integrated mine-to-metals rare earth producer.

By 1982, the US, Australia, India and Brazil accounted for over 95% of world output, with the US bastnaesite deposit supplying over 50% of world output. However, Australia, India, and Brazil continued to export raw rare earth materials to the US and France for further processing. At this time new markets for high-quality, separated rare earths oxides and metals were beginning to develop, ensuring a growing market for rare earths in terms of value. This prompted Molycorp and Rhone-Poulenc to expand their separation and processing facilities.

Throughout the 1980s, China significantly increased their production of rare earth raw materials for sale in the international market. Between 1980 and 1987, Chinese production increased from 8% to 31% of the world total following chaotic and unplanned development. The increasing market share gained by low priced Chinese rare earths in the late 1980s impacted processors elsewhere, especially in the US. For example, in 1988, Research Chemicals, the largest US producer of rare earth metals, were taken over by Rhone-Poulenc. In 1990, Ronson Metals Corporation, mischmetal manufacturers for 75 years, ceased operations and put all of their assets up for sale.

In the late 1980s, the changing pattern of rare earth consumption away from mixed compounds towards high-purity, separated rare earths significantly affected the structure of the rare earth industry. New international entrants in rare earth processing emerged to meet the higher demand for separated materials, including smaller processors in Japan, as well as Treibacher Chemische Werke, Th. Goldschmidt, Rare Earth Products Ltd. and AS Megon in Europe. However, rare earth processing remained dominated by Molycorp, Inc. in the US and Rhone Poulenc, which continued to maintain processing facilities in France and the US.

In 1990 the structure of the Chinese rare earth industry and production and export levels were reorganized by the central government. Afterwards, rare earth producers in China also significantly increased their production of high purity separated rare earths, moving from less than 10% to 50% of production by 1997. Concurrently with these changes, the impacts elsewhere in the rare earth industry were even more significant. In 1993, Dowa Rare Earths Company was forced to close their rare earths plant in Japan because China began producing high quality material at 60% of their market price. In 1994, Nippon Rare Earths, a joint venture between Sumitomo Metal Mining Company of Japan and Rhone Poulenc of France based in Japan, discontinued operations. Mitsubishi of Japan also closed their subsidiary company, Asian Rare Earths based in Malaysia and Mitsui Mining and Smelting in Japan suspended their long term supply contracts. Meanwhile, production of rare earth raw materials from Australia declined as a consequence of growing supplies of rare earth ores from China and restraints concerning disposal of the radioactive wastes associated with monazite extraction, with the price of monazite peaking in 1990. This in combination with increased production in China prompted Rhone-Poulenc and W.R. Grace and Company of the US, two of the major rare earth processors once heavily dependent on Australian ores, to begin purchasing rare earth chlorides from China.

Since the 1990s, China has continued to increase its dominance in the production of rare earth raw materials (Figure 1) and processed rare earths (Table 1). At the same time, production operations elsewhere suffered economic and environmental setbacks. Throughout the 1990s many Japanese companies transferred technology assets to China to secure rare earth supplies, effectively aiding China's move into the integrated production of rare earth products. In March 1998, Molycorp, Inc. suspended production at its Mountain Pass rare earth processing plant due to environmental concerns over its wastewater pipeline. In 1999, Rhodia Rare Earths

consolidated extraction and separation operations to processing facilities in France and China. As a result of this move their US rare earths separation facilities were closed, with much of the equipment being transferred to Rhodia's joint venture with a Chinese rare earth firm. Today, China alone produces about 95% of the world's supply of rare earths, roughly 95,000 mt (USGS, 2005), and nearly 75% of the world's supply of separated rare earths.

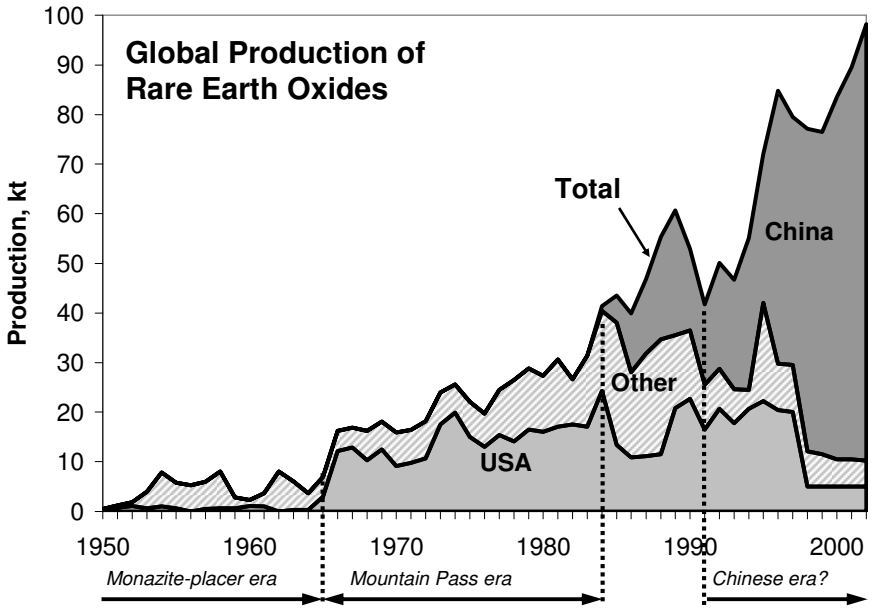

Figure 1 Global production of rare earth oxides, 1950-2003

Table 1 The growth of the Chinese rare earth industry (t REO contained)

	Average Yearly Production				
	1981-90	1991-95	1996-99	2000-02	2003-04
Separated REs % of Processed RE	6%	18%	32%	53%	80%
Separated REs Exported	255	3,400	14,000	19,000	45,000
Proportion of Separated REs in Exports	6%	23%	35%	45%	70%
Total Processed RE Exported	4,300	14,800	40,000	42,200	64,300

2.2 Rare earth technology innovation

The trends in the location of rare earth innovation activities are captured using USPTO patents and shown in Figure 2. The innovation activities captured by the patent data include innovations in the production and separation of rare earths as well as technology applications for which rare earths are a necessary component. The natures of the majority of the patents are of the latter. The figure focuses on innovation in the US precisely because it was originally the dominant region and therefore it had the potential to see greater adverse effects from the internationalization activities. Using these patent trends, Fifarek et al. (2007) find that US leadership in rare earth technology innovation has been eroding since 1990.

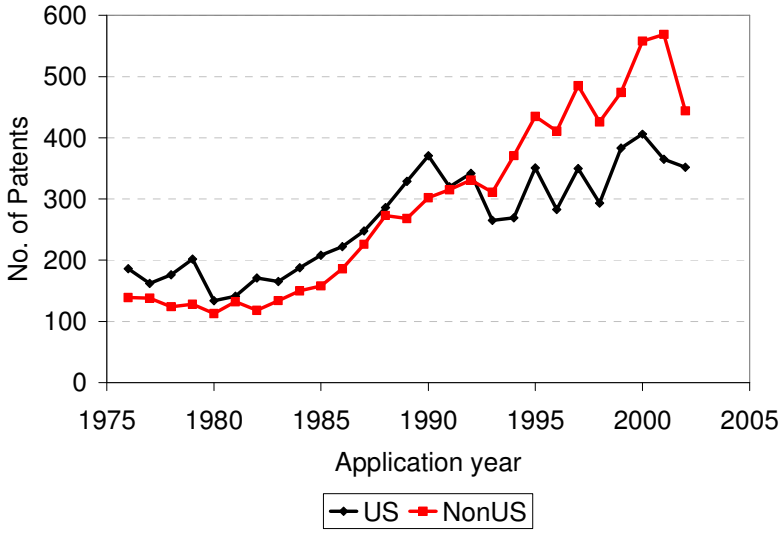

Figure 2 Rare earth technology innovation trends, 1976-2002: US vs. Non-US first inventor home location.

Figure 2 shows the rate of US patenting activity in rare earth based technologies has been declining since 1990. Yet, this trend is not uniform. For example, Figure 3 shows that the US has continued to be a strong leader in innovation in catalyst applications of rare earths, while innovation in magnet technology applications has moved away from the US. The existence of significant differences in response to a strong supply chain internationalization make it an

excellent case to explore what might be critical drivers that lead R&D activities to stay in a region or to follow the supply chain and production relocation.

Interviews with industry leaders and a review of critical industry reports (Roskill, 2001) help formulate a preliminary hypothesis, leading to a model and empirical test. In fact, accounts suggest that R&D activities in rare earth catalyst technology are driven by national and customer environmental policies and strategies. This has fueled a strong continued leadership of the US in innovation activities throughout our study time period, despite the internationalization of the rare earth supply chain. On the contrary, rare earth magnet technology relies heavily on supplier, producer and customer interactions and associated knowledge spillovers among the supply chain, contributing to the movement of innovation away from the US. This contrast and especially the potential role of spillovers lead to the interest in systematic examination of the relationship between knowledge spillovers and the location of innovation activities. Thus, in the subsequent section we begin by examining the theory behind the role of knowledge spillovers in the location of innovation activities.

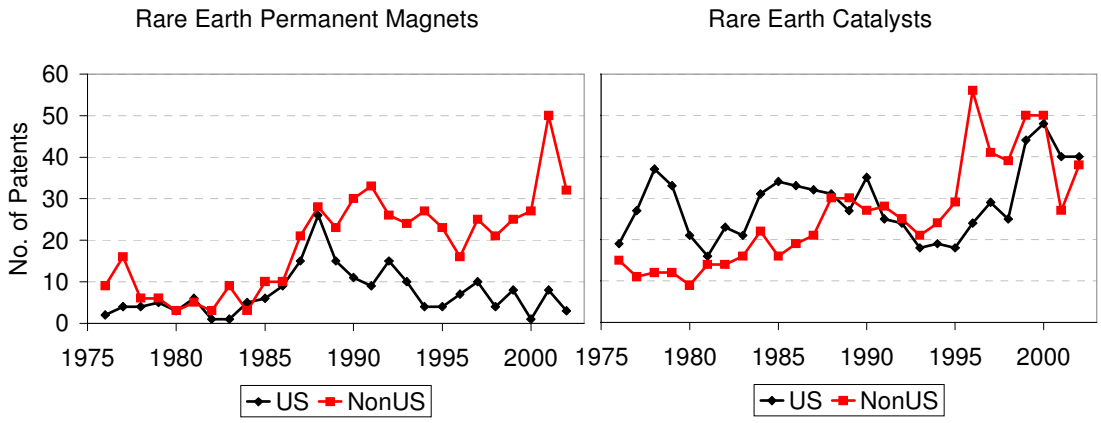

Figure 3 Rare earth magnet and catalyst technology innovation trends, 1976-2002

3 THEORETICAL BACKGROUND: Knowledge spillovers and the location of innovation activities

Existing literature suggests that successful innovation happens through a delicate balance within a system that includes clients, suppliers, R&D units, and the financial system (Lundvall, 1992, Edquist, 1997, Mills et al., 2004, Chapman and Corso, 2005). A similar view is defended by the literature on innovation clusters (Porter, 1990, Porter, 1998) which focuses on the importance of geographic proximity between the organizations of a system for innovation. This is also supported by an emerging perspective that looks at a firm as part of an industrial ecology (Ricart et al., 2004) and identifies the importance of diversity within a geographic location for innovation. The underlying concept for these literatures is the importance of knowledge transfers within supply chains and locations for innovation.

Knowledge spillovers are generated when investments in knowledge creation by one party also benefit other parties without them necessarily having to pay as much for the knowledge. Existing work has generally concluded that knowledge spillovers are geographically localized (Jaffe et al., 1993, Audretsch and Feldman, 1996, Almeida and Kogut, 1999, Branstetter, 2006). The common argument for the geographic localization of knowledge spillovers comes from the notion that knowledge transfer requires effective communication of codified as well as tacit elements. While codified knowledge can easily be transferred across distances, the transfer of tacit knowledge typically requires direct face-to-face interactions between individuals (Zander and Kogut, 1995, Hansen, 2002). This aspect has been explored in particular by measuring the importance and diffusion of knowledge spillovers in patent citations in the US (Jaffe et al., 1993).

The importance of geographic localization in knowledge spillovers has remained a consistent perspective despite significant levels of internationalization over the past 20 years. The pattern of multinational corporate foreign investment in R&D over this time period reflects this consistency albeit in a dichotomous way. Early foreign direct investment was oriented towards exploiting existing capabilities in new foreign markets. As a result, R&D was kept localized in the home region, with some limited remote investment to support foreign manufacturing facilities (Vernon, 1966, Caves, 1971, Hymer, 1976, Rugman, 1981). Later, when R&D investment abroad began to emerge with a stronger presence, it was seen as a tool to access foreign scientific knowledge and technological capabilities considered to be relevant for the firm (Florida, 1997, Kuemmerle, 1999, Serapio et al., 2000). In both contexts, the geographic localization of knowledge spillovers requires local involvement to access knowledge and social networks that facilitate the transfer of external knowledge to the firm. Further studies have found that multinationals consider potential knowledge spillovers opportunities when making R&D investment in foreign subsidiaries (Feinberg and Gupta, 2004) and when locating foreign manufacturing operations (Chung and Alcacer, 2002).

In a more recent paper, Macher and Mowery (2004) go further to suggest that when knowledge spillovers or other capabilities among segments of the value chain matter for innovation, innovation activities are likely to follow the internationalization of supply chain activities. On the other hand, if innovation is not impacted by these spillovers, the location of segments of the industry value chain should have little influence on the location of innovation activities. Yet, this idea has not been directly addressed in the literature.

This research tries to advance our understanding of this notion by analyzing the location of innovation activities in two technology segments that are expected to have different reliance

on knowledge spillovers. In the second section we described the movement of the rare earth element supply chain away from the US and the subsequent changes in the locations of rare earth technology innovation. While overall the location of innovation activities is moving away from the US, some innovation activities remain in the US and others do not. Our empirical analysis aims to examine the nature of knowledge utilized by patenting activity in rare earth catalyst and magnet technology patents.

4 Empirical Analysis

This study uses patents issued by the United States Patent and Trademark Office (USPTO) as a proxy for innovative activity in rare earth catalysts and magnets. There is a substantial prior body of literature arguing that patents are a useful measure of innovative activity (Basberg, 1987, Acs et al., 2002). Although there are well documented limitations to the use of patent data, in particular the fact that not all innovations are patented, Griliches (1990) as well as Patel and Pavitt (1995) have documented that patents are a reasonable proxy for innovation especially in high technology industries. Archibugi and Pianta (1996) claim that patent data can provide estimates of innovative activity at the firm, industry, and country levels, while Pavitt (1985) concludes that patents provide a consistent picture of sectoral patterns of innovative activities.

While many studies support the use of patents as a measure of innovation output, patent citations are also one of the most traceable records to understand critical knowledge flows (Jaffe et al., 1993, Almeida, 1996, Mowery et al., 1996, Stuart and Podolny, 1996). Citations are included in patent applications by the inventor and the patent examiner to help delimit the patent grant by identifying “prior art” of relevance to the focal patent. If one considers a given patent, backward citations listed in the patent can be used to indicate the locations and timing of prior

innovation activities that have generated knowledge useful for generating the given patent. Therefore, one can use citations to look at whether the nature of knowledge utilized for knowledge generation in rare earth catalyst and magnet technology is changing over time. These claims make patent studies a useful measure for innovation within a system boundary, prior knowledge utilized for the generation of new knowledge and a good metric to address the research questions highlighted above.

For this study, two regression models at the patent level are developed to statistically determine if there is a significant change in the propensity for rare earth magnet and rare earth catalyst innovation activities in the US to utilize previously generated local knowledge versus knowledge generated by similar innovation activities abroad following the internationalization of the rare earth supply chain and production activities.

4.1 Data development

In this empirical analysis we use USPTO patenting activity in rare earth magnet and rare earth catalyst technologies over the time period 1976-2002. We utilize patent classifications provided by the USPTO to build the relevant patent datasets for rare earth magnet and catalyst technologies. This is accomplished by locating several patents that perfectly fit into each technology. Following the backward and forward citations of each patent and the citations of these citations, we compile an extensive list of patent classes that may correspond to each technology [more detail on this available from the authors upon request]. From this classification list for each technology, 8 patent classes and 17 patent classes shown in table 3 were chosen to represent rare earth magnet and catalyst technology, respectively. The final patent datasets were then compiled using a keyword search within the previously chosen relevant patent classes. The keyword search was necessary because, for example, in the description of patent class 148/101

we see that a process for generating a ferrite permanent magnet material would qualify. However, we are only interested in process technology for manufacturing rare earth permanent magnet materials. Similarly, in the description of patent class 502/320 we see that a catalyst composition consisting of aluminum would qualify. For this class we are only interested in catalyst compositions consisting of scandium or yttrium. The keyword search returned patents that contained rare earth keywords also shown in Table 2 anywhere within the patent document.

After removing patents assigned to individual inventors, the final combined dataset included 1879 patents of which 637 are rare earth magnet patents and 1242 are rare earth catalyst patents.

Table 2 Keywords and USPTO classifications used to develop patent dataset

Rare Earth Elements	Rare Earth Magnet	Rare Earth Catalyst
Rare Earth	148/301	502/304
Lanthanide	148/302	502/303
Lanthanum, La	148/303	502/302
Cerium, Ce	148/315	502/314
Praseodymium, Pr	148/101	502/320
Neodymium, Nd	148/102	502/322
Promethium, Pm	148/103	502/323
Samarium, Sm	148/122	502/327
Europium, Eu		502/332
Gadolinium, Gd		502/341
Terbium, Tb		502/346
Dysprosium, Dy		502/348
Holmium, Ho		502/351
Erbium, Er		502/354
Thulium, Tm		502/355
Ytterbium, Yb		502/65
Scandium, Sc		502/73
Yttrium, Y		
Lutetium, Lu		

The analysis uses four pieces of information found in patent applications: (1) location information measured by first inventor home location to identify the location of innovation activities, (2) patent application year, (3) complete patent classification list to identify technology classes, and (4) patent citations to identify knowledge used by the given patent. The analysis then uses three pieces of information found in patents listed as citations of patent applications: (1) patent number is used to identify within technology and outside knowledge (e.g., if the patent number listed as a citation for a magnet patent is included in the set of identified magnet patents, then it is identified as within technology knowledge), (2) location information measured by first inventor home location to identify the location of the innovation activity that generated the cited patent, and (3) application year used to identify if the cited patent was applied for within seven years prior to the application of the citing patent.

We limit citations to those applied for seven years prior to the application of the citing patent for two reasons. First, since our patent dataset covers the years 1975 to 2002, citations for a patent applied for in 1978 would have only three prior years of patents from which to draw. However, a patent applied for in 1995 would have 20 prior years of patents from which to draw. Therefore by limiting the citation lag to seven years, all patents included in the citation dataset have an equal number of years from which to draw citations. Second, we are empirically interpreting citations as a measure of the knowledge base which has been expanded by the knowledge contained within the patent as well as the transfer of tacit knowledge or in other words a knowledge spillover among different sets of innovation activities. We assume that citations to patents applied for more than seven years prior represent codified knowledge.

Using the patent information explained above we measure 10 variables for our two datasets of rare earth magnet and rare earth catalyst patent applications between 1982 and 2002.

For each patent we measure the location of the first inventor's home at the country level and the patent application year. We use this information to generate two dummy variables. First, a variable denotes whether the patent's location is in the US or outside of the US (*US*). Second, a variable denotes if the patent's application year was before or after 1990 (*d*), which corresponds to the beginning of Chinese dominance in the production of rare-earth materials. This subsequently led to the internationalization of the rare earth supply chain beginning with raw materials, moving to raw material processing and the production of rare earth technology applications.

For the remaining patent level variables, we first develop a procedure to identify the complete technical classification list of knowledge developed and utilized by a given patent. The technical classifications are based on USPTO patent classifications. The technical classification list begins as the complete list of classifications assigned by the USPTO to the given patent. Then we examine the complete classification list of a patent cited by the given patent. If the classification list of the cited patent contains zero classifications in common with the technical classification list, then the technical classification list for our patent is augmented with the main USPTO classification of the cited patent. If the classification list of the cited patent contains at least one common element, then no additional classifications are included in the technical classification list. The complete technical classification list is determined by examining each patent cited by the given patent.

We then use the technical classification list to categorize the citations made to previous patents into four categories. The first category is prior knowledge included in our patent datasets representing rare earth catalyst or magnet technology, also classified by the USPTO with a matching classification with at least one element of the technical classification list generated for

the given patent and also generated by an innovation activity located in the US. This category is called "US within technology class knowledge (C_{uw})". If the given patent is also generated by an innovation activity located in the US this category represents local technical knowledge spillovers. For a technology where knowledge spillovers matter for innovation activities, we would expect this category to receive the most citations by the given patent.

The second category of knowledge is "NonUS within technology class knowledge (C_{nw})" which is similar to C_{uw} knowledge except that it was generated by innovation activities located outside of the US. If we again consider that the given patent is generated by an innovation activity in the US, then this category represents technical knowledge generated by innovation activities located outside of the US. As suggested by other researchers, as an industry internationalizes and firms gain access to knowledge outside of their home region as well as develop decentralized R&D networks, we would expect the second category of knowledge to receive an increasing amount of citations by the given patent. If knowledge spillovers matter for a technology, we would also expect the second category of knowledge to remain less important than local knowledge measured by the first category of knowledge.

The third and fourth categories of knowledge are "US outside knowledge (C_{uo})" and "NonUS outside knowledge (C_{no})". These categories of knowledge while having at least one classification element in common with the complete technical classification list for the given patent are not included in the patent datasets representing rare earth catalyst or magnet technology. We measure these categories because previous researchers have found that technical knowledge is often used for more than one technology application. All citations to patents in any of the four categories applied for more than 7 years prior to the citing patent's application year

are discounted from the data to avoid citation truncation issues and citation of codified knowledge.

The technical classification list representing the technology class of the patent is then employed on the entire USPTO patent database to measure the number of available patents for citation in each of the four categories relevant for our estimation: US within technology patents (k_{uw}), the number of NonUS within technology patents (k_{nw}), the number of US outside technology patents (k_{uo}), and the number of NonUS outside technology patents (k_{no}). The USPTO patent contains knowledge that is available for our patent to have used if the following two conditions are satisfied (1) if the application year of the USTPO patent occurs less than seven years prior to the application year of our patent and (2) the complete list of classifications assigned to the USPTO patent contains at least one common classification with the complete technical classification list generated for our patent.

Given the USPTO patent is found to be available for our patent to cite, we assign the patent to one of our four categories k_{uw}, k_{nw}, k_{uo}, or k_{no}. If the USPTO patent is contained in our rare earth magnet or rare earth catalyst dataset then it is assigned as an available within technology class patent (k_{uw} or k_{nw}). Otherwise, the USPTO patent is assigned as an available outside technology patent (k_{uo} or k_{no}). If the USPTO patent is from the US then it is assigned as an available US patent (k_{uw} or k_{uo}). Otherwise, the USPTO patent is assigned as an available NonUS patent (k_{nw} or k_{no}).

The above data directly measured and counted using the rare earth magnet and rare earth catalyst data are then combined to form three additional variables. First, for each patent we calculate the percent of knowledge utilized by the given patent that was previously generated by innovation activities located in the US (*perus*) using Equation 1111. We then calculate the

percent of knowledge utilized that was previously generated by innovation activities within the same technology class (*perwithin*) using Equation 2. Finally, we calculate the percent of patents available for citation that originate from local innovation activities (*perus_avail*) or in other words were previously generated by innovation activities in the same country using Equation 3.

$$perus = \frac{C_{uw} + C_{uo}}{C_{uw} + C_{nw} + C_{uo} + C_{no}} \tag{1}$$

$$perwithin = \frac{C_{uw} + C_{nw}}{C_{uw} + C_{nw} + C_{uo} + C_{no}} \tag{2}$$

$$perus\_avail = \frac{k_{uw} + k_{uo}}{k_{uw} + k_{nw} + k_{uo} + k_{no}} \tag{3}$$

The descriptive statistics for the data are shown first for rare earth catalysts and second for rare earth magnets in Table 3. The correlation statistics are shown in Table 4. In the next section, we describe the regressions employed to analyze the nature of knowledge utilized by innovation activities in the US and abroad following the internationalization of supply chain and production activities for rare earth catalyst and magnet technologies. The regression is performed at the patent level.

Table 3 Descriptive statistics

	Variable	Description	Mean	SD	Count	Min	Max
Rare earth Catalyst	C_{lw}	Local within technology citations	0.890	1.473	1242	0	14
	C_{gw}	Global within technology citations	0.975	1.819	1242	0	23
	C_{lo}	Local outside citations	2.114	3.529	1242	0	37
	C_{go}	Global outside citations	1.620	2.576	1242	0	26
	k_{lw}	Available local within technology patents	73.171	53.001	1242	1	232
	k_{gw}	Available global within technology patents	159.825	97.028	1242	1	488
	k_{lo}	Available local outside patents	240.810	404.379	1242	0	10738
	k_{go}	Available global outside patents	426.567	435.365	1242	1	5436
	US	0-1 location dummy variable	0.498	0.500	1242	0	1
	d	0-1 time period dummy variable	0.629	0.483	1242	0	1
	perlocal_avail	Percent local patents available	0.352	0.248	1242	0.001	0.929
	perlocal	Percent local citations made	0.516	0.368	1148	0	1
	perwithin	Percent within technology citations made	0.372	0.369	1148	0	1
Rare earth Magnet	C_{lw}	Local within technology citations	1.557	1.877	637	0	11
	C_{gw}	Global within technology citations	1.176	2.403	637	0	26
	C_{lo}	Local outside citations	0.559	1.115	637	0	11
	C_{go}	Global outside citations	0.367	0.890	637	0	9
	k_{lw}	Available local within technology patents	66.994	49.611	637	1	211
	k_{gw}	Available global within technology patents	64.226	44.110	637	4	273
	k_{lo}	Available local outside patents	144.705	252.862	637	0	2108
	k_{go}	Available global outside patents	226.237	305.349	637	0	3371
	US	0-1 location dummy variable	0.270	0.444	637	0	1
	d	0-1 time period dummy variable	0.647	0.478	637	0	1
	perlocal_avail	Percent local patents available	0.418	0.161	637	0.002	0.735
	perlocal	Percent local citations made	0.601	0.379	570	0	1
	perwithin	Percent within technology citations made	0.727	0.346	570	0	1

Table 4 Correlation statistics

		1	2	3	4	5	6	7	8	9	10	11	12
Rare earth Catalyst	1. C_{lw}												
	2. C_{gw}	0.335											
	3. C_{lo}	0.215	-0.079										
	4. C_{go}	-0.019	0.162	0.230									
	5. k_{lw}	0.342	0.061	0.315	-0.051								
	6. k_{gw}	0.088	0.332	-0.204	0.177	0.052							
	7. k_{lo}	0.154	-0.019	0.534	0.136	0.374	-0.081						
	8. k_{go}	0.046	0.162	0.148	0.410	-0.010	0.431	0.493					
	9. *US*	0.164	-0.124	0.424	-0.075	0.668	-0.479	0.379	-0.246				
	10. *d*	0.064	0.125	0.002	0.198	0.144	0.477	0.143	0.426	-0.121			
	11. *perlocal_avail*	0.215	-0.157	0.433	-0.179	0.613	-0.598	0.366	-0.306	0.886	-0.243		
	12. *perlocal*	0.285	-0.319	0.404	-0.365	0.401	-0.360	0.254	-0.185	0.513	-0.104	0.625	
	13. *perwithin*	0.403	0.458	-0.340	-0.333	0.059	0.203	-0.179	-0.181	-0.140	-0.011	-0.116	-0.098
Rare earth Magnet	1. C_{lw}												
	2. C_{gw}	0.286											
	3. C_{lo}	0.051	0.059										
	4. C_{go}	-0.074	0.174	0.220									
	5. k_{lw}	0.458	-0.010	0.054	-0.190								
	6. k_{gw}	0.186	0.417	-0.064	0.062	0.157							
	7. k_{lo}	-0.016	-0.020	0.418	0.094	0.135	-0.076						
	8. k_{go}	-0.078	0.023	0.413	0.161	0.101	-0.020	0.879					
	9. *US*	-0.062	0.140	0.111	0.142	-0.298	0.138	0.017	-0.071				
	10. *d*	0.204	0.005	0.082	-0.094	0.516	0.384	0.064	0.078	-0.209			
	11. *perlocal_avail*	0.327	-0.175	0.065	-0.177	0.544	-0.328	0.148	-0.124	0.022	0.155		
	12. *perlocal*	0.394	-0.379	0.262	-0.373	0.382	-0.250	0.156	0.059	-0.131	0.193	0.472	
	13. *perwithin*	0.388	0.203	-0.536	-0.418	0.227	0.184	-0.316	-0.356	-0.114	0.078	0.126	0.019

4.2 Regression Analysis

4.2.1 Dependent variable

The dependent variable in the first regression analysis is the percent of US citations (*perus*) made by patent *i*. The regression analysis is conducted separately for rare earth catalyst and magnet technologies. In both rare earth catalyst and magnets, we see from Figure 3 that the percentage of innovation activities conducted in the US is decreasing over time, albeit decreasing significantly more for rare earth magnet technology. Therefore, if knowledge spillovers are important for technology development in either technology, we would expect *perus* to have a decreasing trend over time. However, if a decreasing trend is found for the dependent variable, it may also suggest that for US innovation activities knowledge spillovers are becoming less

important as a global knowledge network develops perhaps driven by the internationalization of supply chain activities and offshoring decisions by US firms. If an increasing trend is found for the dependent variable, it suggests the location of innovation activities is driven by something other than knowledge spillovers because both innovation activities located in the US and abroad are increasingly dependent on knowledge generated by prior US innovation activities.

Since the dependent variable is a percentage that takes the values of 0 and 1 as well as percentages between 0 and 1, we perform the standard logit transformation which is given by

$$L(perus_i) = \ln\left(\frac{perus_i}{1 - perus_i}\right) \tag{4}$$

To directly interpret the coefficients of our regressions, we will need to transform the results back into the original percentage metric. However, before performing the transformation we employ the following equations to substitute for 0 and 100 percent data points which present problems for the logit transformation (Equation 4) and must be adjusted away from the extreme values (Neter et al., 1983).

$$perus_i = \begin{cases} \dfrac{1}{2n_i} & if\ \ perus_i = 0 \\ \dfrac{2n_i - 1}{2n_i} & if\ \ perus_i = 1 \end{cases} \tag{5}$$

where $n_i = C_{uw,\,i} + C_{nw,\,i} + C_{uo,\,i} + C_{no,\,i}$.

4.2.2 Model and critical variables

The purpose of the regression is to statistically determine if there is a significant change in the propensity for rare earth magnet and rare earth catalyst innovation activities in the US to utilize previously generated local knowledge versus similar innovation activities abroad. To perform this evaluation, two independent variables are of critical importance. The first is a 0-1

variable (*US*) that is employed to measure the overall propensity difference for previously generated local knowledge to be utilized by innovation activities in the US and abroad. If knowledge spillovers are significant for the development of rare earth catalyst or magnet technology, we would expect the coefficient for *US* to be positive and significant indicating that innovation activities in the US utilize a higher percentage of knowledge previously generated in the US than abroad. Conversely, a positive and significant coefficient also indicates that innovation activities outside of the US use a lower percentage of knowledge generated by innovation activities in the US or in other words outside of the country of the first inventor listed on the patent.

A second 0-1 variable *(d)* is utilized to capture significant changes in the propensity trends before and after 1990, which corresponds to significant internationalization of the rare earth supply chain and the beginning of Chinese dominance in the production of rare-earth materials. If a positive and significant coefficient is found for *d*, then prior knowledge generated by innovation activities located in the US are more important for the development of new knowledge within the US and abroad.

We also employ one critical control variable (*perus_avail*) that controls for the percent of patents available for citation that were generated by previous innovation activities located in the US. The general idea being that if a patent randomly makes citations to available patents, then we would expect the percent of US citations will be equal to the percent of US patents available for citation. This variable also controls for changes in innovation trends over time. By employing this control variable, we are able to examine the differences in the nature of knowledge being utilized for innovation activities despite the changing shares of patents being generated by a particular location.

A linear regression model is used to estimate the impact of the independent variables on the propensity for a successfully applied patent to utilize knowledge previously generated by US innovation activities. In *Model 1* we test for a significant change in the propensity for innovation activities to utilize US knowledge after 1990 in both the US and abroad.

Model 1a is specified in the following form:

$$\ln\left(\frac{perus_i}{1-perus_i}\right) = \alpha + \beta US_i + \lambda d_i + \varphi perlocal\_avail_i \tag{6}$$

To more closely examine the change in the US, we conduct a second run (*Model 1b*) that isolates the change in propensity for US innovation activities to utilize US knowledge by including the interaction *(US*d)*. This interaction term is critical to determine if any trend in the percent of US knowledge utilized by innovation activities is driven by the importance of knowledge spillovers or by the decreasing percentage of innovation activities conducted in the US.

Model 1b is specified in the following form:

$$\ln\left(\frac{perus_i}{1-perus_i}\right) = \alpha + \beta US_i + \lambda d_i + \gamma(US_i * d_i) + \varphi perus\_avail_i \tag{7}$$

5 Empirical Results and discussion

5.1 Regression results

Table 5 shows the regression results at the patent level for rare earth catalyst and magnet technologies. The first important outcome in *Model 1a* for both technologies is the coefficient for *US* for both rare earth catalysts and magnets is positive and significant (0.9, $p < 0.001$ and 0.6, $p < 0.001$ for catalysts and magnets, respectively). This result indicates that innovation activities

undertaken within the US utilize significantly more knowledge from US innovation activities than those performed outside of the US. This may suggest that knowledge spillovers play an important role in technology development for catalysts and magnets. This result remains consistent in *Model 1b* where we separate out the effect for US innovation activities after 1990 further suggesting that knowledge spillovers may play an important role in these technologies.

Table 5 Regression results at patent level by technology, rare earth magnet and catalyst

Dependent Variable: ln(perus/(1-perus)) *Logistic transform of percent US citations*				
	Rare earth Catalyst		Rare earth Magnet	
Model	1a	1b	1a	1b
US	0.90***	0.87***	0.60***	0.28**
0-1 dummy location	(0.06)	(0.10)	(0.09)	(0.14)
d	0.26***	0.24**	-0.15	-0.35**
0-1 dummy time period	(0.08)	(0.10)	(0.10)	(0.12)
US*d		0.047		0.57**
US after 1990		(0.13)		(0.19)
perlocal_avail	4.26***	4.28***	2.85***	2.67***
Random citation control	(0.32)	(0.32)	(0.54)	(0.54)
Intercept	-2.71***	-2.71***	-1.73***	-1.52***
	(0.20)	(0.20)	(0.24)	(0.25)
Adj R^2	0.34	0.34	0.17	0.18
Observations	1148	1148	570	570
Standard errors in parentheses ** $p \leq 0.05$ *** $p \leq 0.001$				

The next important results deal with the coefficient for the time period dummy variable (*d*). In *Model 1a* and *1b* for rare earth catalysts, we find the coefficient to be positive and significant (0.26, $p < 0.001$ and 0.24, $p < 0.001$, respectively). This indicates that despite the internationalization of the rare earth supply chain after 1990 the percent of knowledge generated by US innovation activities and subsequently used for innovation activities within the US and abroad has increased. This then suggests that knowledge spillovers may not play an important role in catalyst technology development because NonUS. The coefficient for the interaction term

(*US*d*) also confirms this result because it is insignificant. Therefore, this further suggests there is another driver for key catalyst innovation activities to be located in the US.

In contrast, *Model 1a* for rare earth magnets we find an insignificant coefficient for *d* suggesting that after 1990 there is no change in the percent of knowledge generated by previous US innovation activities to be used for magnet technology development despite the internationalization of the rare earth supply chain and production as well as the decrease in the percentage of innovation activities located within the US. This result suggests two possible realities. First, despite the internationalization of the rare earth supply chain and production activities, rare earth magnet innovation activities outside of the US continue to rely on previous knowledge generated by innovation activities in the US. Second, with the internationalization of the rare earth supply chain and production activities, rare earth magnet innovation activities in the outside US now rely more on previous knowledge generated outside of the US, while innovation activities the remain in the US now rely even more on previous innovation activities also conducted in the US. The former reality suggests the globalization of knowledge used for innovation activities for rare earth magnet technology, while the latter suggests the localization of innovation activities and the importance of knowledge spillovers.

The coefficient of *d* and the interaction term (*US*d*) in *Model 1b* for rare earth magnet technology (-0.35, $p < 0.01$ and 0.57, $p < 0.01$, respectively) suggests the localization of knowledge utilized for rare earth magnet innovation activities and the increasing importance of knowledge spillovers. Innovation activities outside of the US after 1990 rely less on knowledge generated by US innovation activities and innovation activities in the US rely more on prior US innovation activities.

Overall, the regression results suggest that locations and technologies respond differently to the internationalization of relevant supply chain and production activities. Furthermore, for technologies where knowledge spillovers are critical for subsequent innovation activities, the internationalization of supply and production activities are likely to drive innovation activities away from the home region. However, our regression analysis does not allow us to distinguish between the following scenarios. If we consider that a share of innovation activities in the US are generated by firms only developing technology for a local market utilizing local knowledge and the rest of the innovation activities generated by firms developing technology for global markets utilizing local and global knowledge. In the first scenario, the propensity for innovation activities in the US to utilize prior knowledge generated in the US could increase if the firms focused on a local technology market begin to use proportionately more US knowledge while the share of innovation activities for local and global markets remains the same. In the second scenario, the share of innovation activities performed for local markets could increase possibly suggesting that firms developing technology for global markets have relocated outside of the home region.

To evaluate these scenarios, we develop an innovation model in the next section. In all of our regressions, the control for random percent of US patents available for citation (*perus_avail*) is statistically significant ($p < 0.001$). This suggests our method of measuring the number, location and technology class of prior innovation activities producing knowledge applicable to an innovation activity is significantly correlated with the actual number of citations in each citation category made by a patent. Therefore, we utilize the number of available patents in each citation category within our model.

5.2 Modeling knowledge spillovers and the location of innovation activities

We consider an innovation *i* in a given technology class *c* (e.g. rare earth magnets) which has taken place in one location. The innovation can be generated by a specific R&D project, by a project manager, or by a product line worker. For every innovation there is a set of prior knowledge generated by other innovations that contributes to innovation's *i* development. To be able to explore the role of spillovers, the set of prior knowledge will be organized in 4 broad categories associated to previous innovation activities conducted by firms within the same main industry, firms outside of this industry, universities, and institutions such as national laboratories and government organizations. The first category is prior knowledge in technology class *c* also generated in location *l*, which is called "local within class knowledge (C_{lw})". For an innovation activity located in the US, this category is analogous to "US within technology class knowledge (C_{uw})" used in the regression analyses. Also, since our regression analyses are only concerned with two locations (US and NonUS), for an innovation activity located outside the US the category C_{lw} is analogous to "NonUS within technology class knowledge (C_{nw})".

The second set of knowledge is "global within class knowledge (C_{gw})" which is defined as prior knowledge in technology class *c* generated outside of location *l*. The third and fourth sets of knowledge are "local outside knowledge (C_{lo})" and "global outside knowledge (C_{go})". These sets of knowledge are outside of the technology class *c* of innovation *i*.

According to the regression analyses for US innovations the percent of local or US citations is significantly correlated with the percent of local or US patents previously generated. Therefore, we use this to suggest that the quantity of knowledge in each of the four categories, C_{lw}, C_{gw}, C_{lo}, and C_{go}, utilized by innovation *i* is a function of the quantity of previously generated knowledge available in each of the matching four categories: "local within class

knowledge (k_{lw})", "global within knowledge (k_{gw})", "local outside knowledge (k_{lo})", and "global outside knowledge (k_{go})", respectively. Again, for innovation activities located in the US the category "local within class knowledge (k_{lw})" is analogous to "US within class knowledge (C_{uw})" used in our regression analyses. We model this function as a series of discrete binomial trials with probability of success δ_j. In other words, if a scientist working on innovation *i* surveyed the available local within class knowledge applicable to the technology being developed, the probability that any single piece of knowledge is utilized by the scientist is δ_j. Therefore, the amount of knowledge utilized by innovation *i* in each of the four categories is

$$C_{lw} = \delta_1 k_{lw} \tag{8}$$

$$C_{gw} = \delta_2 k_{gw} \tag{9}$$

$$C_{lo} = \delta_3 k_{lo} \tag{10}$$

$$C_{go} = \delta_4 k_{go} \tag{11}$$

The probability of success δ_1 and δ_2 for our series of binomial trials are a function of the probability *w* of innovation *i* utilizing prior within technology knowledge. Similarly, the probability of success δ_3 and δ_4 are dependent on the probability (*1-w*) of innovation *i* utilizing prior outside knowledge. Therefore, we define s_j as the probability of a success for our series of binomial trials. It then follows that

$$C_{lw} = w s_1 k_{lw} \tag{12}$$

$$C_{gw} = w s_2 k_{gw} \tag{13}$$

$$C_{lo} = (1 - w) s_3 k_{lo} \tag{14}$$

$$C_{go} = (1 - w) s_4 k_{go} \tag{15}$$

The model further defines two unobservable types of innovations that can occur in location *l*. The first type is local innovation activities that rely proportionately more on prior local knowledge and may in fact be producing technology only for a local market than the second type of innovation activity. For an innovation of this type, we expect $\delta_1 > \delta_2$ given that $k_{lw} = k_{lg}$ and $\delta_3 > \delta_4$ given that $k_{lo} = k_{go}$. The second type of innovation activity in location *l* relies proportionately more on prior knowledge generated in global locations and may in fact be producing technology for a global market. Therefore, we expect $\delta_1 < \delta_2$ and $\delta_3 < \delta_4$, ceteris paribus. For our model, an innovation *i* in location *l* is a local innovation activity with probability *a* and a global innovation activity with probability *(1-a)*. In other words, if we consider a set of innovations in location *l*, then *a* represents the share of innovations in this set resulting from local innovation activities.

Employing a mixture model to incorporate our two unobservable types of innovations, we develop the following system of equations

$$C_{lw} = \lfloor aws_{1,l} + (1-a)ws_{1,g} \rfloor k_{lw} \tag{16}$$

$$C_{gw} = \lfloor aws_{2,l} + (1-a)ws_{2,g} \rfloor k_{gw} \tag{17}$$

$$C_{lo} = \lfloor a(1-w)s_{3,l} + (1-a)(1-w)s_{3,g} \rfloor k_{lo} \tag{18}$$

$$C_{go} = \lfloor a(1-w)s_{4,l} + (1-a)(1-w)s_{4,g} \rfloor k_{go} \tag{19}$$

where

$s_{j,l}$ = probability of success for k_j trials given innovation *i* is a local innovation activity and

$s_{j,g}$ = probability of success for k_j trials given innovation *i* is a global innovation activity.

Following our definition of types of innovation activities, the following conditions must be true,

$$s_{1,l} > s_{1,g} \tag{20}$$

$$s_{2,l} < s_{2,g} \tag{21}$$

$$s_{3,l} > s_{3,g} \tag{22}$$

$$s_{4,l} < s_{4,g} \tag{23}$$

The above relationships (Equations 16-23) hold true for a set of innovations over time period t in location l. To compare sets of innovations in the same technology class from two locations in time period t, we introduce the probability p that any innovation i originates in location l_1. In other words, the share of innovations from location l_1 is p and the share of innovations from location l_2 is $(1-p)$. The above relationships can be compiled in Table 6 to describe the nature of knowledge utilized by sets of innovations in technology class c in two locations in time period t.

Table 6 Relationships describing the nature of knowledge used for innovations in technology class c in time period t.

	Location l_1 (p)		Location l_2 $(1-p)$	
	Local (a)	Global $(1-a)$	Local (b)	Global $(1-b)$
Local within industry knowledge	$paw_1s_{1,l}$	$P(1-a)w_1s_{1,g}$	$(1-p)bw_2s_{5,l}$	$(1-p)(1-b)w_2s_{5,g}$
Global within industry knowledge	$paw_1s_{2,l}$	$P(1-a)w_1s_{2,g}$	$(1-p)bw_2s_{6,l}$	$(1-p)(1-b)w_2s_{6,g}$
Local Outside knowledge	$pa(1-w_1)s_{3,l}$	$P(1-a)(1-w_1)\ s_{3,g}$	$(1-p)b(1-w_2)s_{7,l}$	$(1-p)(1-b)(1-w_2)s_{7,g}$
Global Outside Knowledge	$pa(1-w_1)s_{4,l}$	$P(1-a)(1-w_1)s_{4,g}$	$(1-p)b(1-w_2)s_{8,l}$	$(1-p)(1-b)(1-w_2)s_{8,g}$

where

b = the share of local innovation activities in location l_2,

w_1 = probability of innovation i in location l_1 utilizing prior within technology knowledge and

w_2 = probability of innovation i in location l_2 utilizing prior within technology knowledge.

By directly estimating the model parameters we can compare between time periods by measuring the change in *a* from period *t* to period *t+1*. In other words, for a particular location we estimate the change in the share of innovations generated by local innovation activities based on the nature of knowledge utilized by innovation activities in that location. Such a parameter cannot be estimated by our regression models. However, we do verify that the estimated parameters exhibit results similar to those obtained by the regression models.

5.3 Estimating model parameters

To estimate our model parameters for our eight cases listed in Table 7 we employ the nonlinear programming algorithm called Lipschitz Global Optimizer (LGO) software linked to the General Algebraic Modeling System (GAMS). Within the LGO software we use a global search based solution option called global multistart random search and local search. Due to the nonlinearity of our model and our assumptions pertaining to the process of innovations using prior knowledge, we utilize the software to determine the parameters that best fit our data at the patent level.

Table 7 Cases of technology class, location and time period

Case	Technology Class	Location	Time Period
1	Rare earth magnet	US	1982-1990
2	Rare earth magnet	NonUS	1982-1990
3	Rare earth magnet	US	1991-2002
4	Rare earth magnet	NonUS	1991-2002
5	Rare earth catalyst	US	1982-1990
6	Rare earth catalyst	NonUS	1982-1990
7	Rare earth catalyst	US	1991-2002
8	Rare earth catalyst	NonUS	1991-2002

To match the parameters to our data we minimize the weighted sum of squared errors *(SSE)* objective function shown below.

$$C_{lw} = \lfloor aws_{1,l} + (1-a)ws_{1,g} \rfloor k_{lw} = \delta_1 k_{lw} \tag{24}$$

$$C_{gw} = \lfloor aws_{2,l} + (1-a)ws_{2,g} \rfloor k_{gw} = \delta_2 k_{gw} \tag{25}$$

$$C_{lo} = \lfloor a(1-w)s_{1,l} + (1-a)(1-w)s_{1,g} \rfloor k_{lo} = \delta_3 k_{lo} \tag{26}$$

$$C_{go} = \lfloor a(1-w)s_{2,l} + (1-a)(1-w)s_{2,g} \rfloor k_{go} = \delta_4 k_{go} \tag{27}$$

Minimize *SSE*

$$\begin{aligned} SSE = \sum_i \Bigg\{ & \frac{1}{\sigma_{perlocal}} \left[\frac{\delta_1 k_{lw,i} + \delta_3 k_{lo,i}}{\delta_1 k_{lw,i} + \delta_2 k_{gw,i} + \delta_3 k_{lo,i} + \delta_4 k_{go,i}} - perlocal_i \right]^2 + \\ & \frac{1}{\sigma_{perwithin}} \left[\frac{\delta_1 k_{lw,i} + \delta_2 k_{gw,i}}{\delta_1 k_{lw,i} + \delta_2 k_{gw,i} + \delta_3 k_{lo,i} + \delta_4 k_{go,i}} - perwithin_i \right]^2 + \\ & \frac{1}{\sigma_{C_{lw}}} \left[\delta_1 k_{lw,i} - C_{lw,i} \right]^2 + \frac{1}{\sigma_{C_{gw}}} \left[\delta_2 k_{gw,i} - C_{gw,i} \right]^2 + \frac{1}{\sigma_{C_{lo}}} \left[\delta_3 k_{lo,i} - C_{lo,i} \right]^2 + \\ & \frac{1}{\sigma_{C_{gw}}} \left[\delta_4 k_{gw,i} - C_{gw,i} \right]^2 \Bigg\} \end{aligned} \tag{28}$$

subject to

$$0 < a,\ s_{1,l},\ s_{1,g},\ s_{2,l},\ s_{2,g},\ w < 1 \tag{29}$$

$$s_{1,l} > s_{1,g} \tag{30}$$

$$s_{2,l} > s_{2,g} \tag{31}$$

where for each case in technology, location and time period

$\sigma_{perlocal}$ = standard deviation of the percent of citations made to local patents (*perlocal*)

$\sigma_{perwithin}$ = standard deviation of the percent of citations made to within technology patents (*perwithin*)

$\sigma_{C_{lw}}$ = standard deviation of the number of citations made to local within technology patents (C_{lw})

$\sigma_{C_{lw}}$ = standard deviation of the number of citations made to global within technology patents (C_{gw})

$\sigma_{C_{lo}}$ = standard deviation of the number of citations made to local outside patents (C_{lo})

$\sigma_{C_{go}}$ = standard deviation of the number of citations made to global outside patents (C_{go})

By weighting each sum of squared errors component by $1/\sigma$, we force the parameters to match the data variables with the least variation at the patent level.

5.4 Model parameters

The results for the direct estimation of our model parameters for our eight cases of technology class, location, and time period are shown in Table 8. Due to the nonlinear interactions between the parameters, the first step in interpreting these results is to employ the parameters to build the probability table constructed in Table 6. To compare across columns, time periods, and technologies we normalize each cell in the probability table by the sum of its column. The result shown in Table 9 can be interpreted as the propensity for previous generated knowledge in each of our four categories (k_{lw}, k_{gw}, k_{lo}, k_{go}) to be utilized by our unobservable categories of US_{local}, US_{global}, $NonUS_{local}$, $NonUS_{global}$ innovation activities. For example, 68.9% of the knowledge utilized by US_{local} innovation activities before 1990 was previously generated by local or in other words US innovation activities.

While Table 9 provides a significant amount of information concerning the nature of knowledge utilized by different types of innovation activities in different locations and time periods, we must first confirm that these results suggest similar findings as the regression models already presented. This can easily be accomplished by combining the US_{local} and US_{global} columns as well as the $NonUS_{local}$ and $NonUS_{global}$ columns in the original probability table not

shown through addition. This results in a 2 x 4 probability table that exhibits the propensity for innovation activities in the US and abroad to utilize certain knowledge controlling for the availability of that knowledge. Next, we combine the local citation rows for within technology and outside knowledge also through addition to establish Table 10 which is comparable to our observable data. In Table 10, we see that US and NonUS rare earth magnet innovation activities

Table 8 Model parameters

			Catalyst		Magnet	
			Before 1990	After 1990	Before 1990	After 1990
US Patents	a	Share of local innovations	0.815	0.882	0.453	0.681
	s1	Probability a local innovation cites an available Local patent	0.025	0.017	0.049	0.048
	s2	Probability a global innovation cites an available Local patent	0.018	0.002	0.033	0.037
	s3	Probability a local innovation cites an available Global patent	0.005	0.007	0.015	0.017
	s4	Probability a global innovation cites an available Global patent	0.045	0.031	0.054	0.042
	w1	Probability of citing within indLocaltry patents	0.472	0.661	0.902	0.893
	sse	Sum of Squared Errors Objective Function	1723.307	3.737	528.013	581.955
NonUS Patents	b	Share of local innovations	0.687	0.662	0.344	0.558
	s5	Probability a local innovation cites an available Local patent	0.039	0.022	0.051	0.037
	s6	Probability a global innovation cites an available Local patent	0.007	0.016	0.028	0.005
	s7	Probability a local innovation cites an available Global patent	0.009	0.007	0.005	0.001
	s8	Probability a global innovation cites an available Global patent	0.019	0.015	0.041	0.031
	w2	Probability of citing within indLocaltry patents	0.587	0.705	0.942	0.932
	sse	Sum of Squared Errors Objective Function	850.811	3055.274	563.684	1649.630
	p	Share of Local innovations	0.577	0.452	0.396	0.201

Table 9 Model probability table

Normalized Probability Table (Before 1990)	Catalyst (Period = Before 1990)				Magnet (Period = Before 1990)			
	US innovations		NonUS Innovations		US innovations		NonUS Innovations	
	US_{local}	US_{global}	$NonUS_{local}$	$NonUS_{global}$	US_{local}	US_{global}	$NonUS_{local}$	$NonUS_{global}$
Local within industry knowledge	0.395	0.135	0.478	0.157	0.689	0.342	0.852	0.382
Global within industry knowledge	0.077	0.337	0.109	0.430	0.213	0.560	0.090	0.561
Local Outside knowledge	0.441	0.151	0.336	0.111	0.075	0.037	0.052	0.023
Global Outside Knowledge	0.087	0.377	0.077	0.302	0.023	0.061	0.006	0.034

Normalized Probability Table (After 1990)	Catalyst (Period = After 1990)				Magnet (Period = After 1990)			
	US innovations		NonUS Innovations		US innovations		NonUS Innovations	
	US_{local}	US_{global}	$NonUS_{local}$	$NonUS_{global}$	US_{local}	US_{global}	$NonUS_{local}$	$NonUS_{global}$
Local within industry knowledge	0.468	0.034	0.529	0.367	0.662	0.418	0.905	0.127
Global within industry knowledge	0.192	0.627	0.176	0.338	0.231	0.475	0.026	0.805
Local Outside knowledge	0.241	0.017	0.221	0.154	0.080	0.050	0.066	0.009
Global Outside Knowledge	0.099	0.322	0.073	0.141	0.028	0.057	0.002	0.059

Table 10 Simplified probability table

	Catalyst (Period = Before 1990)		Magnet (Period = Before 1990)	
	US innovations	NonUS Innovations	US innovations	NonUS Innovations
Local knowledge	0.659	0.708	0.526	0.557
Global knowledge	0.341	0.292	0.474	0.443

	Catalyst (Period = After 1990)		Magnet (Period = After 1990)	
	US innovations	NonUS Innovations	US innovations	NonUS Innovations
Local knowledge	0.608	0.671	0.642	0.613
Global knowledge	0.392	0.329	0.358	0.387

become more reliant on local knowledge which matches our regression results for US and NonUS innovation activities after 1990. For rare earth catalyst innovation activities, US and NonUS innovation activities become somewhat less reliant on local knowledge.

Returning to a direct interpretation of the model parameters, we focus on the parameters a, b, w_1, and w_2. For both rare earth catalyst and magnet technologies a increases between the period before 1990 to after 1990. This suggests that the changing nature of knowledge utilized by US innovation activities is driven by an increase in local innovation activities. The variable w_1 is roughly 0.9 before and after 1990 for US rare earth magnet innovations which confirms that within magnet technology knowledge will remain critical for future innovation activities. On the

other hand, the increase in w_1 from before 1990 to after 1990 for rare earth catalyst technology suggests that within catalyst technology knowledge is becoming more important for catalyst innovation activities.

When examining NonUS innovations in rare earth catalysts and magnets, we find that b decreases for catalyst innovation activities but increases for magnet innovation activities. Matching with our regression results, this suggests that rare earth catalyst innovation activities are utilizing more global or US knowledge in the case of our regression while rare earth magnet innovation activities are becoming more dependent on knowledge from previous local innovation activities or NonUS knowledge. The variable w_2 follows a similar pattern as w_1.

However, due to the nature of this nonlinear system of regression equations, the computational models need a set of robustness tests and additional validation to completely analyze our direct estimation of the parameters. One possibility is to use bootstrapping methods to understand the correlations between the parameters and map a larger solution space instead of the global minima presented here in Table 8.

6 Conclusions

These results broadly suggest that if knowledge spillovers among segments of an industry supply chain are important and significant supply chain activities are relocated, then the location of R&D activities are likely to follow the relocation of the supply chain. Furthermore, if most innovations are the result of local knowledge spillovers and innovation increases outside of the local region then some innovation highly dependent such as niche applications on local spillovers will stay while other innovation activities will move to access new knowledge being produced elsewhere.

This paper and these results follow emerging research that is focused on identifying what tasks or jobs will remain in the US and what tasks or jobs are able to be offshored. Leamer and Storper (2001) identify that tasks involving codifiable information can be easily offshored while tasks dependent on tacit information will remain in the US. According to Levy and Murnane (2004), routine tasks are able to be offshored and non-routine takes will remain in the US. Finally, Blinder (2006) suggests there is a difference in the ability to offshore electronic and non-electronic tasks.

In face of these conclusions, important business and public policy challenges arise. First, when making international supply chain and offshoring decisions, firms need to evaluate how important knowledge spillovers are for their innovation dynamics as well as the source location of the critical knowledge. Firms also need to evaluate the internal and external drivers of innovation in their technology arenas.

Existing studies have highlighted how offshoring will affect the operational context of the home base and the need to carefully consider what processes to offshore as a function of this risk (Aron and Singh, 2005). While international supply chains and offshoring may bring innovation opportunities (Quinn, 1999), especially through the contact and interaction with new locations and partners (Ricart et al., 2004), it also brings risks that firms need to evaluate and act upon. In addition, the findings of this research offer a complementary view to the perspective of Chapman and Corso (2005), which assert the need for firms to increasingly plan their innovation within a collaborative supply chain environment. While their discussion focuses mostly on the inter-firm relations, our results suggest that firms need to also consider partner location and the likelihood of knowledge spillovers in the collaborative equation.

Second, while most public policy discussion on offshoring has been related to upgrading worker skills for more value added activities, the results of this paper show that this discussion needs to be reframed to question what innovation activities will stay in a home region and what innovation activities will move outside of the home region. This question is critical because offshoring has the ability to impact innovation dynamics and policy. For example, it has been widely recognized that some of the most important public policies for shaping a nation's level of innovative capacity are those encouraging investment in science and engineering (Furman et al., 2002).Yet, the offshoring practices of many firms could lead one to question public support for basic research because of the difficulty and uncertainty of appropriating a majority of the benefits nationally (Archibugi et al., 1999). This may be further aggravated because offshoring practices may be replacing human capital investment in science and engineering as the go-to business practice for knowledge generation and technology innovation (Hira and Hira, 2005). While it is clear that protectionist public policies to prevent offshoring only weaken the global competitiveness of the US, it is critical to reflect on the role of public policy in a business environment where offshoring practices may lead, not only to job losses, but also a decline in innovation incentives for certain locations and technologies (Fuchs and Kirchain, 2005).

Policies are likely to cluster in two extremes. On the one hand, just like facilitating the transition of workers displaced by offshoring decisions to other areas, policies may need to support quick redeployment of resources from areas of innovation that decline as a result of offshoring into new and more promising work. In the opposite extreme, the government may need to provide support to areas subject to market failure in terms of national private R&D investment because of offshoring decisions, because the existence of local knowledge is considered relevant for the innovation dynamics of the region or nation. It is critical to

understand what characteristics and comparative advantages within regions drive innovation activities to remain localized despite the emergence of international supply chains. In the future, if we hope to maintain a healthy set of R&D activities in the US, it will be critical for policies to help move firms and workers into activities where the interactions between local business, institutions, and the technology environment matters.

Yet, our understanding of these issues is still very limited and further work on how these policies affect a firm's location and offshoring decisions is needed before implementing appropriate public policies to support and sustain US innovation competitiveness. We have identified that the importance or lack of importance of knowledge spillovers influences the risks associated with offshoring for innovation. However, it is reasonable to expect that other criteria influencing offshoring decisions may produce confounding risks and benefits to innovation. Therefore, it is crucial for subsequent research to further explore this issue in more detail.

References

Acs, Z. J., Anselin, L. and Varga, A., 2002. Patents and innovation counts as measures of regional production of new knowledge. Research Policy. 31, 1069-1085.

Almeida, P., 1996. Knowledge sourcing by foreign multinationals: Patent citation analysis in the US semiconductor industry. Strategic Management Journal. 17, 155-165.

Almeida, P. and Kogut, B., 1999. The localization of knowledge and the mobility of engineers in regional networks. Management Science. 45, 905-917.

Archibugi, D., Howells, J. and Michie, J., 1999. Innovation systems in a global economy. Technology Analysis & Strategic Management. 11, 527-539.

Archibugi, D. and Pianta, M., 1996. Measuring technological change through patents and innovation surveys. Technovation. 16, 451-468.

Aron, R. and Singh, J. V., 2005. Getting offshoring right. Harvard Business Review. 83, 135-+.

Audretsch, D. B. and Feldman, M. P., 1996. R&D spillovers and the geography of innovation and production. American Economic Review. 86, 630-640.

Basberg, B. L., 1987. Patents and the Measurement of Technological-Change - a Survey of the Literature. Research Policy. 16, 131-141.

Blinder, A. S., 2006. Offshoring: The next industrial revolution? Foreign Affairs. 85, 113-128.

Branstetter, L., 2006. Is foreign direct investment a channel of knowledge spillovers? Evidence from Japan's FDI in the United States. Journal of International Economics. 68, 325-344.

Caves, R. E., 1971. International Corporations - Industrial Economics of Foreign Investment. Economica. 38, 1-27.

Chapman, R. L. and Corso, M., 2005. From continuous improvement to collaborative innovation: the next challenge in supply chain management. Production Planning & Control. 16, 339-344.

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

Dunning, J. H., 1995. Reappraising the Eclectic Paradigm in an Age of Alliance Capitalism. Journal of International Business Studies. 26, 461-491.

Edquist, C., 1997. Systems of innovation : technologies, institutions, and organizations. Pinter, London ; Washington.

Farrell, D., 2005. Offshoring: Value creation through economic change. Journal of Management Studies. 42, 675-683.

Feenstra, R. C., 1998. Integration of trade and disintegration of production in the global economy. Journal of Economic Perspectives. 12, 31-50.

Feinberg, S. E. and Gupta, A. K., 2004. Knowledge spillovers and the assignment of R&D responsibilities to foreign subsidiaries. Strategic Management Journal. 25, 823-845.

Fifarek, B. J., Veloso, F. and Davidson, C., 2007. Offshoring Technology Innovation: A Case Study of Rare Earth Technology. Journal of Operations Management.

Florida, R., 1997. The globalization of R&D: Results of a survey of foreign-affiliated R&D laboratories in the USA. Research Policy. 26, 85-103.

Fuchs, E. and Kirchain, R., 2005. Changing Paths: The Impact of Manufacturing Off-shore on Technology Development Incentives in the Optoelectronics Industry. Proceedings of the Proceedings of 2005 Annual Meeting of the Academy of Management, Honolulu, HI, pp.

Furman, J. L., Porter, M. E. and Stern, S., 2002. The determinants of national innovative capacity. Research Policy. 31, 899-933.

Griliches, Z., 1990. Patent Statistics as Economic Indicators - a Survey. Journal of Economic Literature. 28, 1661-1707.

Hansen, M. T., 2002. Knowledge networks: Explaining effective knowledge sharing in multiunit companies. Organization Science. 13, 232-248.

Hira, R. and Hira, A., 2005. Outsourcing America: What's behind our national crisis and how can we reclaim American jobs. AMACOM, New York, NY.

Horvit, M., 2004. Delphi among firms sending engineering, research work out of U.S. In: Fort Worth Star-Telegram), Fort Worth, TX.

Hymer, S., 1976. The international operations of national firms : a study of direct foreign investment. MIT Press, Cambridge, Mass.

Jaffe, A. B., Trajtenberg, M. and Henderson, R., 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. Quarterly Journal of Economics. 108, 577-598.

Jaffee, D., 2004. Globalization, offshoring, and economic convergence: a synthesis. In: Understanding Global Outsourcing Conference), New York, NY.

Kuemmerle, W., 1999. The drivers of foreign direct investment into research and development: An empirical investigation. Journal of International Business Studies. 30, 1-24.

Leamer, E. E. and Storper, M., 2001. The economic geography of the Internet age. Journal of International Business Studies. 32, 641-665.

Levy, D. L., 2005. Offshoring in the new global political economy. Journal of Management Studies. 42, 685-693.

Levy, F. and Murnane, R. J., 2004. The new division of labor : how computers are creating the next job market. Russell Sage Foundation; Princeton University Press, New York Princeton, N.J.

Lundvall, B.-Å., 1992. National systems of innovation : towards a theory of innovation and interactive learning. Pinter Publishers, London.

Macher, J. T. and Mowery, D. C., 2004. Vertical specialization and industry structure in high technology industries. Business Strategy over the Industry Life Cycle. 21, 317-355.

Mills, J., Schmitz, J. and Frizelle, G., 2004. A strategic review of "supply networks". International Journal of Operations & Production Management. 24, 1012-1036.

Mowery, D. C., Oxley, J. E. and Silverman, B. S., 1996. Strategic alliances and interfirm knowledge transfer. Strategic Management Journal. 17, 77-91.

Neter, J., Wasserman, W. and Kutner, M. H., 1983. Applied linear regression models. R.D. Irwin, Homewood, Ill.

Patel, P. and Pavitt, K., 1995. Patterns of technological activity: their measurement and interpretation. In: Stoneman, P. (Ed.), Handbook of the economics of innovation and technological changes. Blackwell Publishers Ltd, Oxford, pp. 14-51.

Pavitt, K., 1985. Patent Statistics as Indicators of Innovative Activities - Possibilities and Problems. Scientometrics. 7, 77-99.

Porter, M. E., 1990. The competitive advantage of nations. Free Press, New York.

Porter, M. E., 1998. Clusters and Competition: New agendas for companies, governments, and institutions. In: Porter, M. E. (Ed.), On competition. Havard Business School Press, Boston, pp. pp. 197-287.

Quinn, J. B., 1999. Strategic outsourcing: Leveraging knowledge capabilities. Sloan Management Review. 40, 9-+.

Ricart, J. E., Enright, M. J., Ghemawat, P., Hart, S. L. and Khanna, T., 2004. New frontiers in international strategy. Journal of International Business Studies. 35, 175-200.

Roskill, 2001. Rare Earths and Yttrium (ed. Services, R. I.), London.

Rugman, A. M., 1981. Inside the multinationals : the economics of internal markets. Columbia University Press, New York.

Serapio, M., Dalton, D. and Yoshida, P. G., 2000. Globalization of R&D enters new stage as firms learn to integrate technology operations on world scale. Research-Technology Management. 43, 2-4.

Stuart, T. E. and Podolny, J. M., 1996. Local search and the evolution of technological capabilities. Strategic Management Journal. 17, 21-38.

Vernon, R., 1966. International Investment and International Trade in Product Cycle. Quarterly Journal of Economics. 80, 190-207.

Zander, I., 2002. The formation of international innovation networks in the multinational corporation: an evolutionary perspective. Industrial and Corporate Change. 11, 327-353.

Zander, U. and Kogut, B., 1995. Knowledge and the Speed of the Transfer and Imitation of Organizational Capabilities - an Empirical-Test. Organization Science. 6, 76-92.