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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, the location of innovation activities are not affected by offshoring. Contrary to this view, we suggest that innovation mainly driven by R&D activities can also move abroad as a result of offshoring. We suggest that the movement of innovation abroad will be conditioned by the nature of technology innovation processes, in particular knowledge spillovers, causing some innovation activities to remain in the US while driving other activities away. To explore this idea we conduct an in-depth study of the rare earth industry which provides critical raw materials for numerous technology based applications. This industry is pertinent because it has experienced significant supply chain relocation away from the US and towards developing countries. Using industry accounts and patent information, we examine the impact of the movement of rare earth production from the US to China on the location of rare earth innovation over the past two decades. We find that, while supply chain offshoring has caused rare earth magnet innovation activities to move away from the US, innovation activities in rare earth catalysts remains in the country. Direct observations and industry reports suggest this dichotomous response to supply chain internationalization is driven by the role of knowledge spillovers across value chain actors and the changing nature of technology innovation processes. We employ citations by rare earth technology patents to perform regression analyses and develop a model that empirically validates these critical drivers in the co-location of supply chain and innovation activities.

Keywords: Internationalization, rare earth elements, innovation, knowledge spillovers, offshoring, patents

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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 led 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, batteries and phosphors. However, over the past 20 years, the supply chains of rare earth based applications have been offshored from the US to Asia. In 2006, over 97% of rare earth raw materials originate in China (USGS, 2007). Such changes have led the International Herald Tribune (Lague, 2006) to suggest that "controlling the supply of these minerals gives China a strategic advantage as it seeks to build powerful high-tech industries."

Most research to date on internationalization and offshoring suggests this industry evolution should not negatively impact the ability and involvement of the US in innovation activities related to rare earth elements. 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 about the ability of the US to maintain leadership in rare earth technology based applications (Haxel et al., 2002). In fact, US patenting activity in rare earth based technologies has been declining since 1990, the year by which a significant level of rare earth materials were produced in 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 on a home 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 idea 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. Furthermore, positions in R&D in particular are those thought to be less affected by offshoring and, in fact, considered to be a desired goal in terms of alternative occupations to those being displaced.

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 yet 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 country?*

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 jeopardized by increasing geographic distances between business units as they are offshored. When this happens, managers may subsequently choose to offshore engineering work and R&D so that this work can be more geographically aligned with critical offshore activities. Such a domino effect 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 and the conditions under which they remain in the home country.

This paper aims to advance our understanding of the critical drivers for the movement of innovation activities away from the US following the internationalization of supply chain and production activities; conversely, the paper also identifies drivers that may keep innovation activities in the home country. In particular, it will look at role of knowledge spillovers as an important force explaining these movements. 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- and industry-level unstructured interviews that identify the nature of innovation processes for these technologies and suggest critical drivers that impact the location of innovation activities. The analysis then uses detailed information from a subset of over 75,000 patent applications filed between 1975 and 2002 that document the national location of innovation activities in rare earth catalyst and magnet technology. Specifically, we use citations data from patents to empirically test whether the importance of knowledge spillovers for the innovation process impacts the relocation of innovation activities following the internationalization of supply chain and production activities.

We find that rare earth magnet innovation is moving away from the US while in rare earth catalysts it is remaining in the US, since the internationalization of supply chain and production activities. Furthermore, we find that as the amount of rare earth magnet innovation is increasingly conducted abroad, US rare earth magnet patents rely significantly more on local knowledge, while patenting activity outside of the US rely significantly less. This suggests that innovation highly dependent on local US knowledge remains in the US while other innovation activities highly dependent on knowledge increasingly located abroad move away to access critical knowledge being produced elsewhere. In each case, the location of a focal innovation activity is dependent on the importance of access to local knowledge spillovers. Meanwhile, US and foreign rare earth catalyst patents both rely significantly more on US knowledge following the relocation of the supply chain. This continued leadership of the US in rare earth catalyst innovation suggests that technology characteristics as well as national policies can also drive leading technology developments to continue to be located in a region, even when the supply chain relocates elsewhere.

The conclusions of this paper indicate the need to reframe the discussion on appropriate responses to offshoring. Policy discussion needs to shift away from focusing on moving up the value added chain of activities. Rather, the debate needs to address what characteristics and comparative advantages within nations 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 firms and workers move into activities where the interactions between local business, institutions, and the technology environment matter such that innovation activities are more likely to stay nationally.

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 the co-location of production and innovation activities. In the following section, we introduce our patent data and empirically test for the role of knowledge spillovers on the offshoring of innovation. Next we develop an innovation model that replicates the trends observed in the data, while providing further insight into the role of the nature of innovation processes and knowledge spillovers in the movement of innovation away from the US. 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 (Roskill Information Services Ltd., 1973).

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. Molycorp, Inc. in Mountain Pass was the only fully integrated mine-to-metals rare earth producer. Molycorp was also actively engaged in the production and sale of rare earth products which allowed them to gain a dominant position in the industry (Roskill Information Services Ltd., 1973).

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 (Roskill Information Services Ltd., 1984). However, Australia, India, and Brazil exported raw rare earth materials to the US and France for further processing (Roskill Information Services Ltd., 1988). 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 the supply of rare earths for sale in the international market by producing bastnaesite obtained as a by-product of iron ore mining in Inner Mongolia (Roskill Information Services Ltd., 1984). Between 1980 and 1987, Chinese production increased from 8% to 31% of the world total following chaotic and unplanned development (Roskill Information Services Ltd., 1988). 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, was taken over by Rhone-Poulenc. In 1990, Ronson Metals Corporation, manufacturers of mixed rare earths 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 by Rhone Poulenc, which maintained processing facilities in France and the US (Roskill Information Services Ltd., 1988).

In 1990 the structure of the Chinese rare earth industry as well as production and export levels were reorganized by the central government. Two years later, the Chinese premier, Deng Xiaoping, coined the slogan, “There is oil in the Middle East, there is rare earth in China” (Lague, 2006). By that time, Yujiu (1992) reported 33 Chinese state owned rare earth enterprises (12 mining plants and 21 separation facilities) existed producing about 200 specifications of rare earth materials. Afterwards, rare earth producers in China significantly increased their production of high purity separated rare earths, moving from less than 10% to 50% of production by 1997 (Roskill Information Services Ltd., 1998). 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 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. Consequently, the price of monazite peaked in 1990 (Roskill Information Services Ltd., 1994). 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 processing plant due to environmental concerns over its wastewater pipeline (Roskill Information Services Ltd., 1998). Then 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 (Roskill Information Services Ltd., 2001).

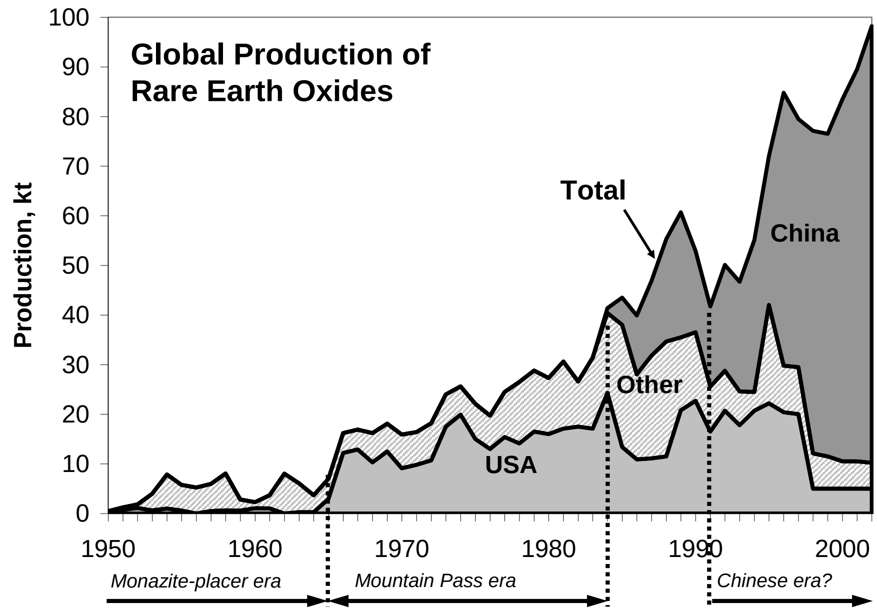

Figure 1 Global production of rare earth oxides, 1950-2003 (Haxel et al., 2002)

Table 1 The growth of the Chinese rare earth industry (mt rare earth oxides contained) (Kingsnorth, 2006)

	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

Since establishing a significant share of the market, China has continued to invest in rare earth materials. For example, the Chinese Ministry of Science and Technology announced a national basic research program in 1997 where one of the high-priority projects was "Basic research in rare earth materials" (Lei, 1998). Today, China alone produces over 97% of the world's supply of rare earths, roughly 120,000 mt (USGS, 2007), and nearly 75% of the world's supply of separated rare earths.

To get an overall picture of the geographic changes in the rare earth industry including extraction, separation, supply and demand, and technical applications we examined 11 editions of rare earth industry reports compiled by Roskill Information Services located in the UK. The reports were published between 1973 and 2001. According to these comprehensive reports, after 1990 China is the most critical geographic location for the rare earth industry, as shown in Figure 2. Increasing levels of Chinese dominance in rare earth materials led researchers at the United States Geological Service to suggest that “the United States is in danger of losing its longstanding leadership in many areas of REE technology” (Haxel et al., 2002). The danger is rising because "China is cornering the market for an obscure group of minerals [rare earths] that are vital to high-technology industry" (Lague, 2006). To better understand the impact of the movement of rare earth supply chain and production activities away from the US on the location of higher value added activities, we examine the location of rare earth innovation activity using patents in the next section.

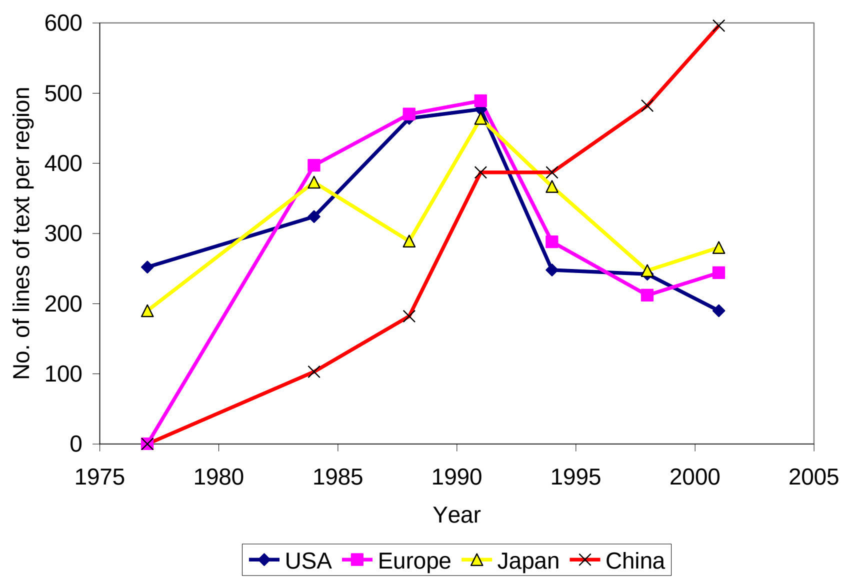

Figure 2 Rare earth industry reports 1977-2001, authors’ own review

(Roskill Information Services Ltd., 1977; 1984; 1988; 1991; 1994; 1998; 2001).

2.2 Rare earth technology innovation

The trends in the location of rare earth innovation activities are identified using USPTO patents and shown in Figure 3. The patent data include two types of innovation activities: (1) innovations in the extraction, production and separation of rare earths, and (2) innovations in technology applications for which rare earths are a necessary component. The majority of the patents are of the latter type. Figure 3 focuses on innovation in the US precisely because it was originally the dominant country in rare earth patents and therefore it had the potential to see greater adverse effects from supply chain internationalization. Using these patent trends, Fifarek et al. (2007) find that US leadership in rare earth technology innovation has been eroding since 1990.

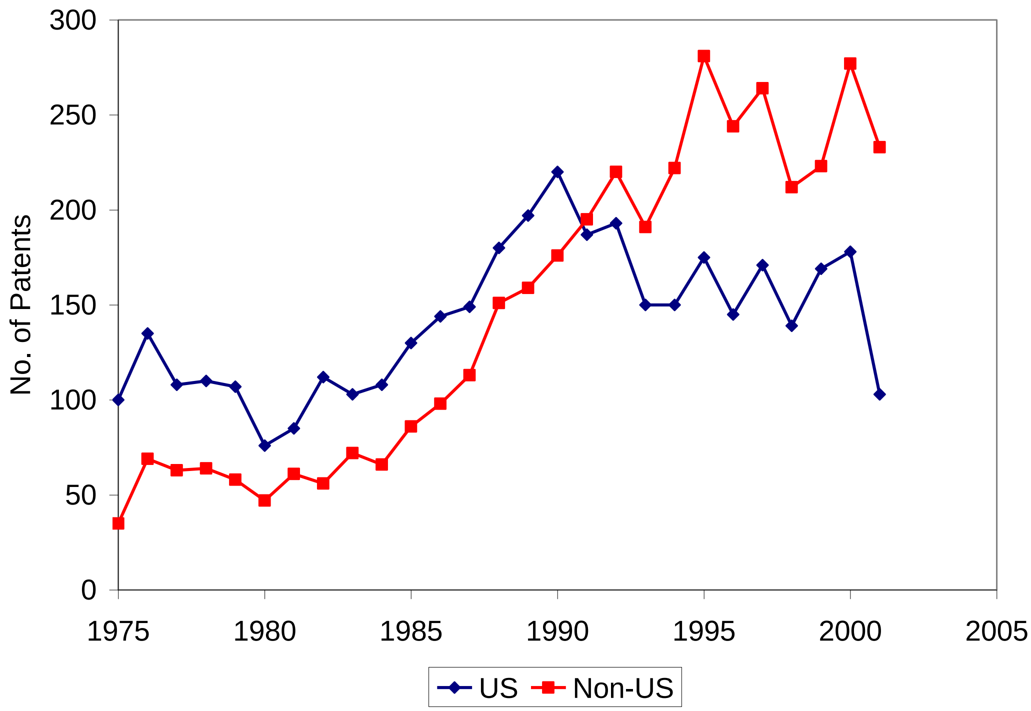

Figure 3 Rare earth patent trends, 1974-2002: US vs. NonUS (Fifarek et al., 2007).

Figure 3 shows that the rate of US patenting activity in rare earth based technologies has been, on average, declining since 1990. Yet, this trend is not uniform across rare earth technology applications. For example, Figure 4 shows that the US has continued to be a strong leader in innovation in catalyst applications of rare earths, while innovation in permanent magnet technology applications has moved away from the US. The dichotomy of these responses to significant supply chain internationalization makes these two technologies excellent case studies to explore critical drivers that lead R&D activities to stay in a home country or to follow the offshore relocation of supply chain and production activities.

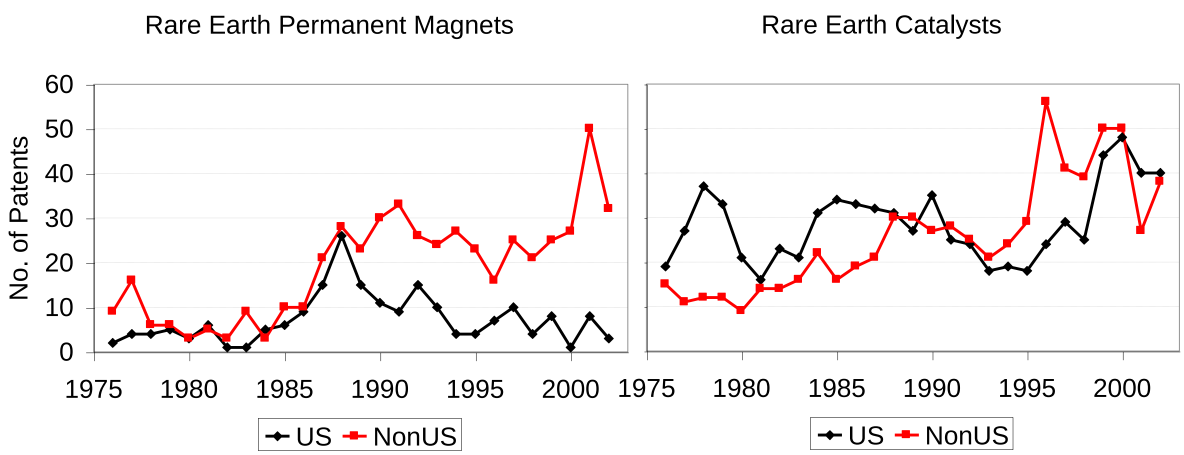

Figure 4 Rare earth permanent magnet and catalyst technology innovation trends, 1976-2002.

Interviews with firm and industry leaders and a review of critical industry reports help formulate a preliminary hypothesis, leading to an empirical test and model. The two major uses in terms of volume and value of rare earth catalyst compounds are petroleum fluid cracking catalysts and automobile exhaust emission control. Production of these technology based applications is dominated by large global companies that maintain manufacturing facilities throughout the world. For example, the US corporation Engelhard, which produces both major applications of rare earth catalysts, maintains production facilities in USA, Europe, South Africa, Korea, Japan, India, and China (Roskill Information Services Ltd., 2001).

Accounts by industry representatives suggest that R&D activities in rare earth catalyst technology are driven by cost reduction efforts, as well as national environmental policies and strategies. The role of policy in catalyst innovation is confirmed by Lee et al. (2007), which find that US *technology-forcing* auto emission standards induced technology innovation in, among other things, catalytic converters for which rare earths are a critical component. Accounts also suggest that rare earth catalysts are a modular component for automobiles and petroleum refining. Over 50% of the cracking units in operation in Europe in the 1990s were reported to be using catalysts that had only been introduced in the prior three years (Roskill Information Services Ltd., 2001), indicating that new catalysts replace older catalysts without requiring significant upgrades or redesigns for petroleum refining processing equipment. Similarly, auto catalysts are an exhaust after-treatment that can be developed separately from the rest of the automobile, allowing corporations to specialize in the production and development of auto catalysts. These properties of rare earth catalyst technology allow the separation of supply chain and production activities from innovation activities. Furthermore, the key rare earth elements used for catalysts are Lanthanum and Cerium, which are the most abundant and least expensive rare earth materials, thereby discounting the importance of interactions between particular raw material suppliers and catalyst producers. These characteristics have fueled a strong continued leadership of the US in rare earth catalyst innovation activities throughout our study time period evident in Figure 4, despite the movement of rare earth supply chain and production activities away from the US.

On the contrary, since the development of rare earth permanent magnet materials, their use in conventional applications often requires a complete redesign of the product to fully take advantage of the unique and powerful properties of samarium-cobalt (SmCo) and neodymium-iron-boron (NdFeB) magnet alloys (Roskill Information Services Ltd., 1998). In fact, Trout and Zhilicihev (1999) suggest some of the potential benefits of the high energy product and low raw material cost of NdFeB magnet materials have yet to be achieved because of design flaws in technical applications of NdFeB magnets.

Unlike rare earth catalyst manufacturers that continue to maintain US production facilities, permanent magnet manufacturers have discontinued their US operations. Meanwhile, the Chinese share of NdFeB magnet production increased from 14.4% in 1988 to nearly 40% in 1997 (Dongpei and Qiming, 1999). Trout (2002) suggests that the powerful combination of locally available rare earths, inexpensive labor and a desire to make value-added products has led to a large percentage of rare earth magnets and products containing magnets being exported from China. Such trends have quickly altered the availability of tacit knowledge related to producing and supporting permanent magnet products and innovation in the US. Informal conversations with one firm representative revealed that removing manufacturing from the US has also led to the removal of over 90% of domestic R&D activities on rare earth permanent magnet materials.

These observations suggest rare earth magnet technology relies heavily on supplier, producer and customer interactions and associated knowledge spillovers across the supply chain, which are easier to leverage if the iterating parties are geographically close. This helps explain the movement of innovation away from the US following the internationalization of rare earth supply chain and production activities, evident in Figure 4.

Magnequench, Inc. is a clear firm-level example of the impact of the internationalization of supply chain and production activities. Originally a business unit within General Motors, Magnequench filed a key patent application on the material composition of NdFeB permanent magnets in 1982. Four years later, they opened a large permanent magnet production facility in Indiana. The company quickly became the top producer of neodymium magnetic powders and magnets and leader in innovation in the NdFeB permanent magnet market. However, the internationalization of their supply chain and production activities quickly impacted the location of their innovation activities. In 2002, three years after establishing production facilities in China, Magnequech closed the Indiana production facility. Meanwhile, the company established a centralized R&D technology center in Research Triangle Park, North Carolina. Then in 2004, Magnequench finally offshored their R&D technology center to Singapore in 2004. They cited geographic proximity to the source of raw materials and downstream users as the main reasons for their offshoring decisions (Magnequench, 2005).

These contrasts between the critical factors in the natures of rare earth catalyst and magnet innovation processes lead to the need for systematic examination of drivers that impact the location of innovation activities following the internationalization of supply chain and production activities. In this paper, we utilize patent citation data to examine the role of knowledge spillovers as such a driver. In the case of rare earth catalysts, innovation activities can be pursued independently from upstream suppliers, suggesting a limited opportunity for the transfer or spillover of knowledge across different actors in the supply chain. But in the case of rare earth magnets, the full potential benefits of new magnetic materials are only realized in combination with complementary innovations throughout the supply chain. Rare earth magnet innovation activities thus require the continuous exchange of knowledge across suppliers, producers and customers, or, in other words, there exists a high degree of opportunity for knowledge spillovers. Thus, in the next section we begin by examining the theory behind the role of knowledge spillovers in the location of innovation activities.

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 further 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 studies is the importance of knowledge transfers within systems and locations for innovation.

A transfer of knowledge is identified as a knowledge spillover when investments in knowledge creation by one party also benefit other parties without them necessarily having to pay as much for the same 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).

Regardless, both codified and tacit technical knowledge are people and institution embodied, making these types of knowledge difficult to transfer and often requiring close interactions between physical systems and individuals (Greeno and Moore, 1993). The local nature of knowledge transfer 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 centralized 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 multinational companies consider potential knowledge spillovers as 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 critically dependent on local knowledge 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.

To further explore the notion put forward by Macher and Mowery (2004) and advance our understanding regarding the conditions under which companies choose to relocate their innovation activities, we consider two technology segments expected to have different reliance on knowledge spillovers. In fact, while overall figures suggest that the location of rare earth innovation activities is moving away from the US, one can observe that some innovation activities remain in the US and others do not. Our empirical analysis examines citations by patenting activity in rare earth catalyst and magnet technologies to assess the role of knowledge spillovers as a critical driver for these trends.

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, researchers claim that patent data can provide estimates of innovative activity at the firm, industry, sectoral and country levels (Pavitt, 1985; Archibugi and Pianta, 1996). Griliches (1990) as well as Patel and Pavitt (1995) have documented that patents are a reasonable proxy for innovation especially in high technology industries.

While many studies support the use of patents as a measure of innovation output, this study is specifically interested in citations by a focal patent to knowledge contained within previous patents. According to several researchers, 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. Backward citations listed in a 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 measure the nature of knowledge utilized for technology development in rare earth catalyst and magnet technology over time. These claims make patent studies a useful measure for innovation within a system boundary, as well as an assessment of prior knowledge utilized for the generation of new knowledge, and a good metric to address the role of local knowledge spillovers in the movement of innovation activities following the internationalization of supply chain and production activities.

For this study, two regression models at the patent level are developed to statistically determine (1) if knowledge spillovers play a role in the nature of innovation processes for rare earth catalyst and magnet technology and (2) whether knowledge spillovers are a critical driver in the movement of innovation activities away from the US following the internationalization of the rare earth supply chain and production activities. If knowledge spillovers across the supply chain matter for the movement of innovation activities, then we should expect find that the relocation of the supply chain to Asia will command an increase in the share of innovation activities conducted outside of the US, which will simultaneously rely less on US knowledge, while innovation activities that do remain in the US will rely proportionally more on US knowledge.

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. From this classification list for each technology, 8 patent classes and 17 patent classes shown in

Table 2 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 to eliminate patents within a USPTO class that did not focus specifically on innovations dealing with rare earth elements. For example, in the description of patent class 148/101 a process for generating a ferrite permanent magnet material would qualify for inclusion in our dataset. However, the keyword search eliminates this patent, since we are only interested in process technology for manufacturing rare earth permanent magnet materials. The keyword search returned patents that contained rare earth keywords also shown in the first column of

Table 2 anywhere within the patent document.

Table 2 Keywords and USPTO classifications used to develop patent dataset

Rare earth elements	Rare earth Magnets	Rare earth Catalysts
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		

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.

The analysis uses four pieces of information found in patent applications: (1) location of innovation activities, defined as the home location of the first inventor, (2) patent application year, (3) complete patent classification list to identify technology classes, and (4) patent citations to identify knowledge used by the focal patent. The analysis then uses three pieces of information found in patents listed as citations: (1) patent number is used to identify "within technology" and "outside technology" 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 of the innovation activity that generated the cited patent, defined as the home location of the first inventor, 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 applications submitted within 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 application 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, thus limiting errors due to data truncation. Second, we are interpreting citations as "spillover knowledge," or a measure of the new knowledge generated by a previous innovation activity and recorded in a patent that is subsequently utilized by a focal patent applied for at a later date. Thus, we follow the approach of Fifarek et al. (2007), where citations to patents applied for more than seven years prior are assumed to represent only codified knowledge, thus beyond the need for the transfer of tacit knowledge associated with spillovers. Moreover, as shown in Fifarek et al. (2007), minor changes to the cutoff year are not expected to influence the results.

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. The first dummy variable denotes whether the patent's location is in the US or outside of the US (*US*). The second dummy variable denotes if the patent's application year was before or after 1990 (*d*), which corresponds to the emergence of the Chinese as a significant producer of rare earth materials. As described earlier, Chinese production 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. We base our choice of the year for the second dummy variable on trends in the production of raw materials (Figure 1) and in rare earth industry reports (Figure 2) because these trends are exogenous to changes in the nature of innovation processes in rare earth catalyst and magnet technology.

The next four variables categorize the citations made by the focal patent. The first variable measures the number of citations made to patents contained within our main datasets representing rare earth catalyst or magnet technology and also generated by an innovation activity located in the US as measured by the location of the first inventor. This variable is called "US within technology knowledge (C_{uw})". If the focal patent is also generated by an innovation activity located in the US this variable represents local technical knowledge spillovers. For a technology where within technology knowledge spillovers matter for innovation activities, we expect this variable to receive the most citations by the focal patent.

The second variable for citations is "NonUS within technology 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 focal patent is generated by an innovation activity in the US, then this variable represents technical knowledge not easily accessible due to the increased difficulty of transferring knowledge. As suggested by other researchers, as an industry internationalizes and firms gain access to knowledge outside of their home country as well as develop decentralized and global R&D networks, we would expect this second variable of knowledge to receive an increasing amount of citations by focal patents over time. If knowledge spillovers matter for a technology, we would also expect the second citation variable to remain less important than local knowledge measured by the first citation variable.

The third and fourth variables for citations are "US outside technology knowledge (C_{uo})" and "NonUS outside technology knowledge (C_{no})". These variables measure citations to patents that are not included in the patent datasets representing rare earth catalyst or magnet technology. We measure these variables because previous researchers have found that technical knowledge is often used for more than one technology application. As already mentioned, all citations to patents measured by any of the four variables but 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.

For the remaining patent level variables, we first develop a procedure to identify the complete technical classification list of knowledge developed and cited by a focal patent. This list is based on USPTO patent classifications. We begin with the complete list of classifications assigned by the USPTO to the focal patent. Then we examine the complete classification list of a patent cited by the focal patent. If the classification list of the cited patent contains no classifications in common with the first list, then the technical classification list for our focal 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 added to the list of classifications for the focal patent. This procedure is repeated for every patent cited by the focal patent to obtain the complete list of USPTO classifications that describe the knowledge contained in the focal patent.

We use the technical classification list on the entire USPTO patent database to measure the number of available patents for citation that correspond to each of the four citation variables relevant for our estimation: "available US within technology patents (A_{uw})", "available NonUS within technology patents (A_{nw})", "available US outside technology patents (A_{uo})", and "available

NonUS outside technology patents (A_{no})". A USPTO patent contains knowledge that is available for the focal 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 the focal 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 the focal patent.

Given the USPTO patent is found to be available for the focal patent to cite, the USPTO patent is measured by one of our four variables A_{uw}, A_{nw}, A_{uo}, or A_{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 patent (A_{uw} or A_{nw}). Otherwise, the USPTO patent is assigned as an available outside technology patent (A_{uo} or A_{no}). If the USPTO patent is from the US then it is assigned as an available US patent (A_{uw} or A_{uo}). Otherwise, the USPTO patent is assigned as an available NonUS patent (A_{nw} or A_{no}).

The above data directly measured and counted using the rare earth magnet and rare earth catalyst data are then combined to form two additional variables. First, for each focal patent we calculate the percent of knowledge utilized by the focal patent that was previously generated by innovation activities located in the US (*perus*) using Equation 1. We then calculate the percent of patents available for citation that originate from US innovation activities (*perus_avail*) using Equation 2.

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

$$perus\_avail = \frac{A_{uw} + A_{uo}}{A_{uw} + A_{nw} + A_{uo} + A_{no}} \tag{2}$$

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	Min	Max
Rare earth Catalysts[ar]	C_{uw}	US within technology citations	0.852	1.410	0	14
	C_{nw}	NonUS within technology citations	1.013	1.817	0	19
	C_{uo}	US outside technology citations	2.382	3.648	0	37
	C_{no}	NonUS outside technology citations	1.351	2.069	0	22
	A_{uw}	Available US within technology patents	109.684	42.526	3	263
	A_{nw}	Available NonUS within technology patents	122.733	75.668	1	345
	A_{uo}	Available US outside technology patents	345.696	399.305	0	10645
	A_{no}	Available NonUS outside technology patents	306.044	338.430	1	5377
	US	0-1 location dummy variable	0.498	0.500	0	1
	d	0-1 time period dummy variable	0.629	0.483	0	1
	perus_avail	Percent US patents available	0.543	0.118	0.332	0.929
	perus[b]	Percent US citations made	0.543	0.355	0	1
Rare earth Magnets[c]	C_{uw}	US within technology citations	0.837	1.392	0	11
	C_{nw}	NonUS within technology citations	1.896	2.584	0	26
	C_{uo}	US outside technology citations	0.350	0.864	0	11
	C_{no}	NonUS outside technology citations	0.578	1.125	0	9
	A_{uw}	Available US within technology patents	41.082	22.821	1	106
	A_{nw}	Available NonUS within technology patents	89.460	53.944	5	229
	A_{uo}	Available US outside technology patents	151.937	210.334	0	2329
	A_{no}	Available NonUS outside technology patents	214.129	336.653	1	3102
	US	0-1 location dummy variable	0.270	0.444	0	1
	d	0-1 time period dummy variable	0.647	0.478	0	1
	perus_avail	Percent US patents available	0.388	0.086	0.176	0.657
	perus[d]	Percent US citations made	0.326	0.350	0	1

a: Observations = 1242 unless otherwise specified
b: Observations = 1148
c: Observations = 637 unless otherwise specified
d: Observations = 570

Table 4 Correlation statistics

		1	2	3	4	5	6	7	8	9	10	11
Rare earth Catalysts[ar]	1. C_{uw}											
	2. C_{nw}	0.39										
	3. C_{uo}	0.23	-0.09									
	4. C_{no}	0.06	0.15	0.38								
	5. A_{uw}	0.21	0.30	-0.01	0.12							
	6. A_{nw}	0.15	0.37	-0.07	0.20	0.80						
	7. A_{uo}	0.08	0.04	0.41	0.29	0.11	0.15					
	8. A_{no}	0.08	0.18	0.28	0.40	0.26	0.44	0.84				
	9. US	0.20	-0.15	0.34	0.04	-0.03	-0.13	0.09	0.01			
	10. d	0.03	0.16	0.01	0.23	0.24	0.57	0.23	0.43	-0.12		
	11. perus_avail	0.07	-0.28	0.21	-0.21	-0.33	-0.73	-0.02	-0.38	0.26	-0.59	
	12. perus[b]	0.26	-0.36	0.39	-0.27	-0.15	-0.29	0.08	-0.07	0.45	-0.16	0.42
Rare earth Magnets[c]	1. C_{uw}											
	2. C_{nw}	0.45										
	3. C_{uo}	0.23	0.07									
	4. C_{no}	0.00	0.03	0.24								
	5. A_{uw}	0.40	0.34	0.06	-0.08							
	6. A_{nw}	0.20	0.36	-0.11	-0.01	0.65						
	7. A_{uo}	0.01	-0.04	0.23	0.37	-0.04	0.06					
	8. A_{no}	-0.02	-0.04	0.15	0.38	-0.04	0.08	0.95				
	9. US	0.23	-0.04	0.29	-0.00	0.04	-0.18	-0.01	-0.05			
	10. d	-0.02	0.16	-0.07	0.06	0.34	0.64	0.05	0.09	-0.21		
	11. perus_avail	0.06	-0.19	0.25	0.02	-0.07	-0.52	0.17	-0.01	0.25	-0.47	
	12. perus[d]	0.43	-0.28	0.40	-0.22	0.09	-0.19	-0.3	-0.09	0.34	-0.23	0.33

a: Observations = 1242 unless otherwise specified
b: Observations = 1148
c: Observations = 637 unless otherwise specified
d: Observations = 570

4.2 Regression Analysis

4.2.1 Dependent variable

The dependent variable in the first regression analysis is the share of US citations (*perus*) made by a focal patent *i*. The regression analysis is conducted separately for rare earth catalyst and magnet technologies. For both rare earth catalysts and magnets, we see from Figure 4 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 as innovation activities conducted abroad utilize local knowledge also located abroad. However, this decreasing trend 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 *perus*, 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

$$L(perus_i) = \ln\left(\frac{perus_i}{1 - perus_i}\right) \tag{3}$$

To directly interpret the coefficients of our regressions, we will need to transform the results back into the original percentage metric.[1]

4.2.2 Model and critical variables

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

[1] Before performing the logit transformation (Equation 3) substitutions are necessary for 0 and 100 percent data points which present problems for the transformation and must be adjusted away from the extreme values. We employ the remedies discussed in Neter, J., Wasserman, W. and Kutner, M.H. (1983). *Applied linear regression models*. Homewood, Ill., R.D. Irwin.

to measure the overall propensity difference for previously generated US 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 rely proportionally more on knowledge previously generated in the US than abroad controlling for the amount of knowledge available in each region. 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, which is outside of the country of the first inventor listed on foreign focal patents.

A second 0-1 variable (*d*) is utilized to capture significant changes in the propensity trends before and after 1990, which corresponds to emergence 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 is 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. Assuming that the probability of citing an available US patent is equal to the probability of citing an available NonUS patent and that our focal patent randomly makes citations, then the expected percent US citations (*perus*) will equal the percent of US patents available (*perus_avail*) for citation. This variable also controls for changes in the share of knowledge available in countries over time, which is driven by changes in the share of innovation activities located in these countries.

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:

$$\ln\left(\frac{perus_i}{1-perus_i}\right)=\alpha+\beta US_i+\lambda d_i+\varphi perus\_avail_i \tag{4}$$

To determine whether any trend in US innovation activities using US knowledge is driven by knowledge spillovers as opposed to a decreasing percentage of innovation activities in the US, we include an interaction term (*US*d*). This term is used in *Model 1b*, specified as follows:

$$\ln\left(\frac{perus_i}{1-perus_i}\right)=\alpha+\beta US_i+\lambda d_i+\gamma\left(US_i*d_i\right)+\varphi perus\_avail_i \tag{5}$$

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 observation is that the coefficient for *US* is positive and significant for both rare earth catalysts and magnets across all models. Thus innovation activities undertaken within the US rely significantly more on knowledge from other US innovation activities than on knowledge from activities performed outside the country – given what would be expected from a random draw based on availability. This suggests that knowledge spillovers play a role in technology development for both catalysts and magnets.

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 relate to 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, knowledge generated in the US in this area has grown in importance for subsequent innovation activities both in the US and abroad. This suggests that, while knowledge spillovers play an important role in catalyst technology development in the US, innovation activities located abroad are also increasingly utilizing knowledge generated in the US in spite of the increased difficulty of transferring tacit knowledge across large geographical distances. The importance of US knowledge for innovation activities abroad confirms that, as industry observations previously described in Section 2.2 imply, technology characteristics as well as national environmental policies may play a more significant role than knowledge spillovers in driving leading technology developments in rare earth catalysts to continue to be located in the US and subsequently used for rare earth catalyst innovation activities located in the US and abroad. This drives multinational corporations that represent a significant percentage of catalyst technology development to monitor competitor and institutional innovation activities in the US. The coefficient for the interaction term (*US*d*) also confirms this result because it is insignificant, suggesting that changes in the nature of innovation processes for rare earth catalysts are similar despite their geographic location and not significantly impacted by the movement of supply chain and production activities away from the US.

In contrast, in *Model 1a* for rare earth magnets we find an insignificant coefficient for *d*. At a first glance this could suggest that, despite the internationalization of the rare earth supply chain, production and innovation activities after 1990, there is no change in the role that the knowledge generated by previous US innovation activities plays in new magnet technology development in the US or abroad. Yet, the results of *Model 1b* for rare earth magnet technology imply a slightly different perspective. As it can be seen, the *d* coefficient is negative and significant (-0.35, $p < 0.01$), while the interaction term (*US*d*) is positive and significant (and 0.57, $p < 0.01$) Thus, what we observe suggests the growing importance of local knowledge spillovers for rare earth magnet innovation activities located in the US as well as abroad. There is a compound effect, whereby innovation activities outside of the US after 1990 rely less on knowledge generated by US innovation activities (and more on knowledge generated outside the US), while innovation activities in the US rely proportionally more on prior US innovative effort.

Overall, the regression results imply that locations and technologies respond differently to the internationalization of relevant supply chain and production activities. Furthermore, for technologies where supply chain knowledge spillovers are critical for subsequent innovation activities, innovation is likely to follow the internationalization of supply and production away from the home country. Our results for magnets are consistent with direct industry observations previously described that indicate supplier, producer and customer interactions and associated knowledge spillovers are critical in the industry, thus suggesting that access to knowledge spillovers within the supply chain played a role in the movement of innovation offshore. Meanwhile, US rare earth magnet innovation activities that remain in the US after 1990 shows evidence of a relative increase in local knowledge spillovers, despite the growth in offshoring innovation activities after 1990.

Although the regression results are consistent with the notion that access to knowledge and subsequent spillovers can drive the location of innovation activities, at least for some activities, it is important to note that they are also consistent with an alternate explanation based on unobserved heterogeneity. Our interpretation of the regression results assumes that the nature of rare earth magnet innovation processes, i.e., the average propensity for focal patents to cite available US patents, remains consistent before and after 1990. This assumption drives our interpretation of the regression results to suggest that rare earth magnet innovation activities that otherwise would have been performed in the US have relocated offshore to access critical knowledge moved offshore by the internationalization of supply chain and production activities. If the nature of the innovation processes in the US changed after 1990, so that all innovative activity simply relies more on local knowledge, rather than global knowledge, the role of spillovers in driving the increasing share of innovation activities located offshore ought to be discounted. In this competing explanation, the decreasing share of rare earth magnet innovation conducted within the US evident in Figure 4 would be the result of something other than the relocation of innovation activities to access local knowledge spillovers.

Thus, to distinguish between our competing explanations, we develop a model with an underlying structure for the nature of innovation processes which (1) explicitly identifies the role of knowledge spillovers, (2) controls for the nature of innovation processes to rely on local knowledge throughout our study time period, and (3) is able to replicate the key regression results that US rare earth catalyst and magnet innovation activities rely more on US knowledge after 1990. Through the model, we expect to be able to identify the innovation activities that rely on proportionately more knowledge generated abroad make up a decreasing share of US innovation activities following the internationalization of supply chain, production, and innovation activities. Such a result suggests that these innovation activities have relocated abroad to minimize the cost of supplier, producer and customer interactions and therefore maximize access to associated knowledge spillovers. Meanwhile, US innovation activities that rely on knowledge generated by previous local innovation activities remain in the US, thereby making up an increasing share of US innovation activities. A description and specification of the model is found in the following section.

5.2 Modeling knowledge spillovers and the location of innovation activities

To capture a process by which innovation activities move away from a home country, we create a model that considers a focal innovation (i) in a given technology class (c) (e.g., rare earth magnets), shown in the left column of Figure 5. The focal innovation is generated by an activity that takes place in time period t and is located in a home country (e.g., located in US) with probability p_t. For this focal innovation under consideration, there exists a set of prior local knowledge generated by other activities also located in the same home country (A_l). Similarly, there exists a relevant set of prior global knowledge located outside of the home country (A_g). Prior knowledge is developed by firms within the same technology class arena, firms outside of this technology arena, universities, and institutions such as national laboratories and government organizations.

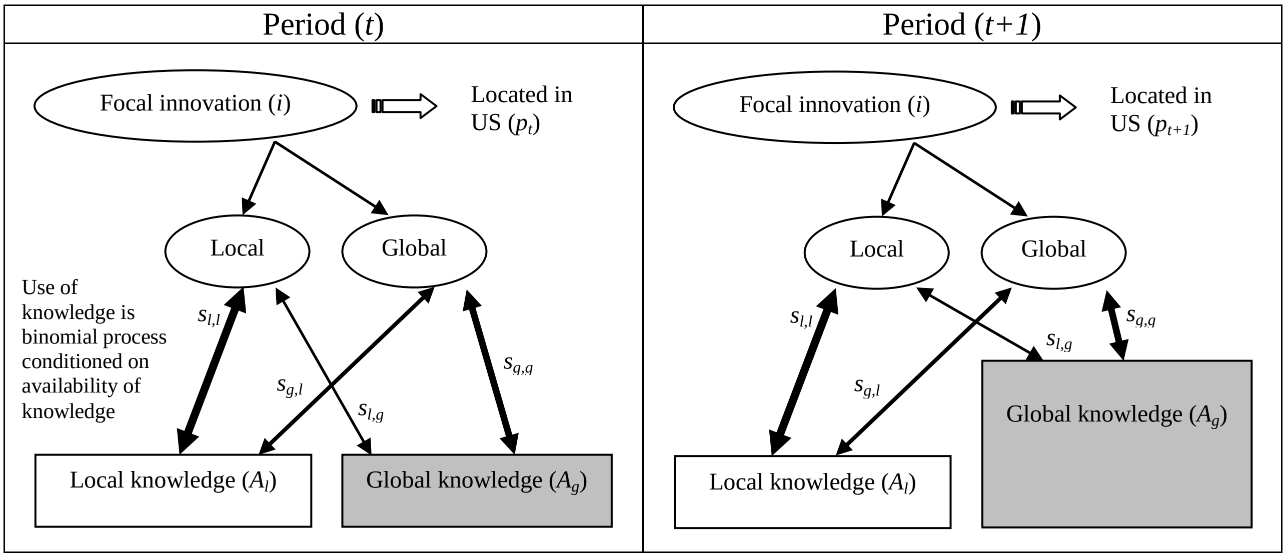

Figure 5 Model diagram

In our model, we consider that the focal innovation can be categorized based on the nature of the innovation process for the activity from which it was generated. To make the analysis more tractable, we will simply define two types of activities that are differentiated by their propensity to use various sets of prior knowledge. The first activity type is defined as *local innovation* activities which rely mostly on local knowledge spillovers and therefore have a greater propensity to use available local knowledge. The second activity type is defined as *global innovation* activities which have a greater propensity to use available knowledge located abroad. The propensities for local and global innovation activities to use local and global knowledge describe the nature of the innovation process for each activity.

We then model the innovation processes (quantity of prior local and global knowledge utilized by the focal innovation) as a series of discrete binomial trials conditioned on the knowledge available locally and abroad. As shown in Figure 5, a single piece of knowledge drawn from the set of prior knowledge pertaining to the focal innovation is utilized by the focal innovation with probability s. In other words, if a scientist working on our focal innovation activity, categorized as a *local innovation* activity, surveyed the available *local knowledge* (A_l) applicable to the technology being developed, the probability that any single piece of such knowledge is utilized by the scientist is $s_{l,l}$. Similarly, any single piece of the set of *global knowledge* (A_g) is utilized by that same *local innovation* activity with probability $s_{l,g}$. The expected quantity of knowledge utilized by the focal innovation is then the probability of utilization multiplied by the quantity of available knowledge or $s_{k,j}*A_j$, where k defines if the innovation is generated by a *local* or *global innovation* activity and j signifies local or global knowledge. By matching our data to this model using a mixture method described in the next section, we are able to estimate the nature of innovation processes for *local* and *global innovation* activities and the share of each activity before the internationalization of supply chain, production and innovation activities.

Of crucial importance to our study, the model allows an analysis of what may happen to innovation due to the movement of supply chain, production and innovation activities away from the home country. In the right hand side of Figure 5, we show an example of such analysis for period $t+1$. There are two critical changes between period t and $t+1$ associated with these movements. First, in period $t+1$ the probability of the focal innovation being generated by an innovation activity located in the home country (e.g., the US) decreases ($p_{t+1} < p_t$) due to supply chain internationalization. This then impacts the second critical change, which is the relative increase in the share of available global knowledge that can be utilized by the focal innovation (the A_l and A_g in Figure 5). Finally, it is important to reflect on how the nature of local and global innovation processes (the $s_{x,x}$ variables) change across time. Our baseline analysis will force this structure to remain the same for local innovations (e.g., $s_{l,l,t} = s_{l,l,t+1}$). In this context, changes in the average probability of innovation activities within our focal country to cite local knowledge will be the result only of a change in the shares of *local* and *global innovation* activities, driven by supply chain relocation and not the structure of the innovation process in how it relies on local vs. global knowledge. In the case of rare earth magnets, if the observed trends in the regression analysis presented in Section 4.2.2. are indeed the result of an underlying knowledge spillovers process, we expect the model to be able to also show an increase in the share of *local innovation* activities in time period *t+1*, which follows the internationalization of supply chain and production activities.

To empirically estimate the probabilities and shares in the model and draw comparisons with the regression analyses, we organize the set of prior knowledge into 4 broad categories similar to the variables described in Section 4.1. The first category is prior knowledge in technology class *c* also generated in the home location, which is called "local within technology knowledge (C_{lw})". Prior knowledge measured by this variable is available locally which permits face-to-face interactions which facilitate the transfer of critical tacit knowledge. The individuals actively participating in the focal innovation also have the absorptive capacity to utilize the prior knowledge in this category because the knowledge is contained within a similar technology space. For an innovation activity located in the US, this category is analogous to "US within technology knowledge (C_{uw})" used in the regression analyses.

The second set of knowledge is "global within technology knowledge (C_{gw})" which is defined as prior knowledge in technology class *c* generated outside of location *l*. While this second set of knowledge is contained within the same technology space as the focal innovation (*i*), the geographical distance increases the difficulty of transferring critical tacit knowledge. The third and fourth sets of prior knowledge are “local outside technology knowledge (C_{lo})” and “global outside technology knowledge (C_{go})”. These sets of knowledge are outside of the technology class *c* of the focal innovation. Again, the proximity of local outside technology knowledge to the location of the focal innovation permits the effective communication of critical tacit knowledge.

We then organize the sets of previously generated knowledge available to the focal innovation in four matching categories: “available local within technology knowledge (A_{lw})”, “available global within technology knowledge (A_{gw})”, “available local outside technology knowledge (A_{lo})”, and “available global outside technology knowledge (A_{go})”, respectively. Again, for innovation activities located in the US the category “available local within technology knowledge (A_{lw})” is analogous to “available US within technology knowledge (A_{uw})” used in our regression analyses.

Since we organize knowledge as within or outside a particular set of technology knowledge, the expected quantity of knowledge in any category is also a function of the probability for the focal innovation to utilize prior within technology knowledge (*w*) and prior outside knowledge (*1-w*). We then employ a mixture model to incorporate our two unobservable types of innovations, where the focal innovation is categorized as a *local innovation* activity with probability *a* and a *global innovation* activity with probability (*1-a*). Therefore, the expected number of citations made to local within technology patents will a combination of the probability of *local* and *global innovation* activities citing local within technology patents and the probability that the focal innovation is identified as a *local* and a *global innovation* activity. If we consider a set of innovations in a home country after finding the optimal parameters for the model, then *a* represents the share of focal innovations resulting from *local innovation* activities.

Finally, to maintain the nature of innovation processes in time period *t* and *t+1*, we introduce three parameters. We utilize a dummy variable (d) where d=1 if the focal innovation takes place in time period *t+1* and zero otherwise. We then employ

a_d = change in the share of local innovation activities in time period *t+1* and

w_d = change in the propensity for innovation activities to utilize within technology knowledge.

Therefore, it follows that our model is specified by the following system of equations that describe the quantity of knowledge utilized by innovation activities in a home country in time period *t* and *t+1*.

$$C_{lw,i} = \left\lfloor (a + a_d d_i)(w + w_d d_i) s_{l,l} + (1 - (a + a_d d_i))(w + w_d d_i) s_{l,g} \right\rfloor A_{lw,i} \quad (6)$$

$$C_{gw,i} = \left\lfloor (a + a_d d_i)(w + w_d d_i) s_{g,l} + (1 - (a + a_d d_i))(w + w_d d_i) s_{g,g} \right\rfloor A_{gw,i} \quad (7)$$

$$C_{uo,i} = \left\lfloor (a + a_d d_i)(1 - (w + w_d d_i)) s_{l,l} + (1 - (a + a_d d_i))(1 - (w + w_d d_i)) s_{l,g} \right\rfloor A_{o,i} \quad (8)$$

$$C_{no,i} = \left\lfloor (a + a_d d_i)(1 - (w + w_d d_i)) s_{g,l} + (1 - (a + a_d d_i))(1 - (w + w_d d_i)) s_{g,g} \right\rfloor A_{o,i} \quad (9)$$

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

$$s_{l,l} > s_{l,g} \quad (10)$$

$$s_{g,l} < s_{g,g} \quad (11)$$

The above relationships have been compiled in

Table 6 to describe the nature of knowledge utilized by sets of innovations in technology class *c* in time period *t* and *t+1*.

Table 6 Relationships describing the nature of knowledge used for innovations in technology class *c* in time periods *t* and *t+1*.

	Time period (*t*)		Time period (*t+1*)	
Percent US innovations	p_t		p_{t+1}	
% innovation activities	Local (*a*)	Global (1-a)	Local $(a+a_d)$	Global $(1-(a+a_d))$
Local within technology knowledge	$ws_{l,l}$	$ws_{l,g}$	$(w+w_d)s_{l,l}$	$(w+w_d)s_{l,g}$
Global within technology knowledge	$ws_{g,l}$	$ws_{g,g}$	$(w+w_d)s_{g,l}$	$(w+w_d)s_{g,g}$
Local outside technology knowledge	$(1-w)s_{l,l}$	$(1-w)s_{l,g}$	$(1-(w+w_d))s_{l,l}$	$(1-(w+w_d))s_{l,g}$
Global outside technology knowledge	$(1-w)s_{g,l}$	$(1-w)s_{g,g}$	$(1-(w+w_d))s_{g,l}$	$(1-(w+w_d))s_{g,g}$

Our model summarized in

Table 6 captures key parameters that describe the nature of innovation activities and the role of knowledge spillovers in the movement of innovation away from a home country. In making innovation decisions firms recognize not only the location of markets for their technology, but also the relative share of innovation activities (*p*) being conducted within their home location. Over time the share of innovation activities conducted within their home location influences the availability of local knowledge (A_{lw} and A_{lo}) and global knowledge (A_{gw} and A_{go}). Understanding the markets for their technology and the availability of knowledge for their innovation activities, firms further recognize the importance of local knowledge spillovers (s_l) or the ability to access global knowledge networks (s_g). The process of interaction between these parameters then impacts the propensity of innovation activities to be conducted in the home location.

In the next section, we describe our empirical estimation of the model parameters for rare earth catalyst and magnet technology located in the US. We are specifically interested in the change in the share of *local innovation* activities (a_d) in the US from period *t* to period *t+1*. In other words, for US rare earth catalyst and magnet technology we empirically estimate the change in the share of innovations generated by *local innovation* activities controlling for the nature of innovation processes. If knowledge spillovers are important, we expect to see the share of *local innovation* activities increase when the share of available local knowledge is decreasing. Such a finding would suggest that the innovation activities that remain in the home country do so because the critical knowledge needed also remains in the home country. Meanwhile, innovation activities which depend on local knowledge that has followed the offshoring of supply chain and production activities will move away from the home country and towards another location where these critical knowledge spillovers are more easily accessible.

Such a parameter represents unobserved heterogeneity in our regression models. With this model specification, we can control for this unobserved heterogeneity in the nature of innovation processes between time periods in our regression model and measure changes in the share of *local* versus *global innovation* activities in a particular location. We are also able to verify that the estimated parameters exhibit results similar to those obtained by the regression models. The model therefore allows the direct examination of the importance of knowledge spillovers driving innovation away from the US following the internationalization of supply chain and production activities.

5.3 Estimating model parameters for US rare earth magnet innovation activities

The innovation model for innovation activities is based on the set of Equations 6-9 containing a set of parameters $\Theta \equiv \left(a_j, a_{d,j}, s_{l,l}, s_{l,g}, s_{g,l}, s_{g,g}, w_j, w_{d,j}\right)$ that can be estimated through a weighted OLS fit of the data to the model. Because the set of Equations 6-9 is nonlinear, the optimization was performed numerically by employing the nonlinear programming algorithms called Lipschitz Global Optimizer (LGO) and Branch-And-Reduce Optimization Navigator (BARON) linked to the General Algebraic Modeling System (GAMS).

We employ our innovation model for innovation activities located in the US. We do not employ the model for innovation activities located outside of the US because these activities are occurring in a diverse set of locations including Japan, China, Germany and France. This creates an additional level of unobserved heterogeneity which is not controlled for by our model specification. As previously explained the data are patent applications for rare earth catalyst and magnet technology located in the US between 1982 and 2002.

To match the parameters to our data we minimize the weighted sum of squared errors *(SSE)* objective function shown below in Equation 12.

Minimize *SSE*

$$SSE = \sum_i \left\{ \frac{1}{\sigma_{C_{lw}}} \left[\delta_{lw} k_{lw,i} - C_{lw,i}\right]^2 + \frac{1}{\sigma_{C_{gw}}} \left[\delta_{gw} k_{gw,i} - C_{gw,i}\right]^2 + \frac{1}{\sigma_{C_{lo}}} \left[\delta_{lo} k_{lo,i} - C_{lo,i}\right]^2 + \frac{1}{\sigma_{C_{gw}}} \left[\delta_{gw} k_{gw,i} - C_{gw,i}\right]^2 \right\} \tag{12}$$

where

$$\delta_{lw} = \left[(a + a_d d_i)(w + w_d d_i)s_{l,l} + (1 - (a + a_d d_i))(w + w_d d_i)s_{l,g}\right] \tag{13}$$

$$\delta_{gw} = \left[(a + a_d d_i)(w + w_d d_i)s_{g,l} + (1 - (a + a_d d_i))(w + w_d d_i)s_{g,g}\right] \tag{14}$$

$$\delta_{lo} = \left[(a + a_d d_i)(1 - (w + w_d d_i))s_{l,l} + (1 - (a + a_d d_i))(1 - (w + w_d d_i))s_{l,g}\right] \tag{15}$$

$$\delta_{go} = \left[(a + a_d d_i)(1 - (w + w_d d_i))s_{g,l} + (1 - (a + a_d d_i))(1 - (w + w_d d_i))s_{g,g}\right] \tag{16}$$

$\sigma_{C_{lw}}$ = standard deviation of the number of local within technology patents cited (C_{lw}),

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

$\sigma_{C_{lo}}$ = standard deviation of the number of local outside technology patents cited (C_{lo}), and

$\sigma_{C_{go}}$ = standard deviation of the number of global outside technology patents cited (C_{go}), and

subject to the following additional constraints to ensure that the optimal solution Θ is consistent with model assumptions,

$$0 < a,\, a_d,\, s_{l,l},\, s_{l,g},\, s_{g,l},\, s_{g,g},\, w,\, w_d < 1 \tag{17}$$

$$s_{l,l} > s_{l,g} \tag{18}$$

$$s_{g,l} < s_{g,g}. \tag{19}$$

$$0 < a + a_d < 1 \tag{20}$$

$$0 < w + w_d < 1 \tag{21}$$

By weighting each sum of squared errors component by the inverse of the standard deviation of the dependent variable, we force the parameters to match the first moment of the citation variables with the least variation at the patent level.

5.4 Model parameters

The results for the direct optimization of our model parameters for rare earth catalyst and magnet technology innovation activities located in the US before and after 1990 are shown in Table 7.[2] Due to the nonlinear interactions between the parameters, several steps are required to fully interpret the model results. The first step is to employ the optimal parameters to fill in the values of the probability table constructed in

[2] 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 7.

Table 6. These values are found in

Table 8. The second step involves calculating the conditional probability of utilizing local knowledge for *local* and *global innovation* activities in both time periods. Local knowledge consists of the variables that measure "local within technology knowledge" and "local outside technology knowledge". Since these categories are mutually exclusive, the conditional probability of citing local knowledge is found by adding the probability of citing knowledge in each category and then dividing by the total probability of citing any available knowledge, where the total probability of citing available knowledge is the sum of each column in

Table 8. As expected the conditional probabilities (see Table 9) for citing local knowledge for *local* and *global innovation* activities are equal in both time periods since our model controls for the nature of innovation processes.

In the third step, we calculate the weighted average conditional probability of utilizing local knowledge in both time periods using the percent of *local* and *global innovation* activities as the weights. This is a critical robustness test in which we compare the model results to our regression results. These values are discussed below. Given that our model results mirror the regression results, in the fourth step, we directly interpret the change in the share of *local innovation* activities. After analyzing the results for rare earth catalysts and magnets separately, we then draw comparisons between the two technologies.

First, we examine the results for rare earth magnets. According to our model, rare earth magnet innovation activities located in the US can be categorized as *local* or *global innovation* activities depending on the nature of their innovation processes. Table 9 shows that for *local* and *global innovation* activities the conditional probability of utilizing local knowledge is 0.788 and 0.455, respectively. These natures of innovation processes are maintained in both time periods. Before 1990, 22% of rare earth magnet innovation activities are categorized as *local innovation* activities (a = 0.223), while after 1990, 62% are categorized as *local innovation* activities ($a + a_d$ = 0.620). Using these shares as weights, the weighted average conditional probability of citing local (US) knowledge is 0.529 before 1990 and increases to 0.661 after 1990. This is consistent with our previous regression results in *Model 1b* for rare earth magnet technology, which suggested the localization of knowledge utilized for US innovation activities through the coefficient of the interaction term (*US*d*) (0.57, $p < 0.01$).

In the model we see, as expected, that the share of *local innovation* activities increases from 22% to 62%. Moreover, this is observed while keeping the overall structure of the innovation processes the same before and after 1990 and allowing only the probability that a focal innovation activity is located in the US to change (and consequently the relative share of available knowledge in the US and abroad). So, what is happening is that the innovation activities that stay in the US are precisely those that rely proportionately more on knowledge located in the US while those that rely on knowledge now located abroad move away from the US (due to the transition of the supply chain to Asia).

Both the regressions and modeling suggest that on average US rare earth magnet innovation activities are more dependent on local knowledge spillovers after 1990. But the model allows measurement of the share of innovation activities with different natures of innovation processes that are behind this increase in the utilization of US knowledge after 1990. This lends support to the idea that the decrease in the percent of rare earth magnet innovation activities located in the US is driven by the importance of knowledge spillovers across the supply chain and subsequent movement of innovation activities abroad to access knowledge.

Table 7 Model parameters

		Magnet	Catalyst
a	Share of local innovations	0.223	0.574
a_d	Change in share of local innovation after 1990	0.397	-0.235
$s_{l,l}$	Probability a local innovation cites an available Local patent	0.049	0.040
$s_{l,g}$	Probability a global innovation cites an available Global patent	0.037	0.001
$s_{g,l}$	Probability a local innovation cites an available Global patent	0.013	0.007
$s_{g,g}$	Probability a global innovation cites an available Global patent	0.045	0.012
w	Probability of citing within technology patents	0.906	0.426
w_d	Change in probability of citing within technology patents after 1990	-0.011	0.214
p_t	Share of US innovations before 1990	0.396	0.577
p_{t+1}	Share of US innovations after 1990	0.201	0.452
ESS	Estimated sum of squares	1667.297	13371.092

RSS	Residual sum of squares	2457.612	15931.290
r^2	Coefficient of Determination	0.404	0.456

Table 8 Model probability tables

Rare earth Magnets				
	Before 1990		After 1990	
Percent US innovations	40%		20%	
	Local	Global	Local	Global
% innovation activities	22%	78%	62%	38%
Local within technology knowledge	0.044	0.034	0.044	0.034
Global within technology knowledge	0.012	0.041	0.012	0.040
Local outside technology knowledge	0.005	0.004	0.005	0.004
Global outside technology knowledge	0.001	0.004	0.001	0.005
Rare earth Catalysts				
	Before 1990		After 1990	
Percent US innovations	58%		45%	
	Local	Global	Local	Global
% innovation activities	57%	43%	34%	66%
Local within technology knowledge	0.017	3.8e-4	0.025	0.001
Global within technology knowledge	0.003	0.005	0.004	0.007
Local outside technology knowledge	0.023	0.001	0.014	3.2e-4
Global outside technology knowledge	0.004	0.007	0.002	0.004

Table 9 Conditional probability of citing knowledge for US_{local} and US_{global} innovation activities

Rare earth Magnets				
	Before 1990		After 1990	
	Local	Global	Local	Global
% innovation activities	22%	78%	62%	38%
Local knowledge	0.788	0.455	0.788	0.455
Global knowledge	0.212	0.545	0.212	0.545
Rare earth Catalysts				
	Before 1990		After 1990	
	Local	Global	Local	Global
% innovation activities	57%	43%	34%	66%
Local knowledge	0.852	0.071	0.852	0.071
Global knowledge	0.148	0.929	0.148	0.929

Second, we examine the results for rare earth catalysts. Table 9 shows that for *local innovation* activities, the conditional probability of utilizing local knowledge is 0.852, while for *global innovation* activities it is 0.071. These natures of innovation processes are again maintained in both time periods. Before 1990, 57% of rare earth catalyst innovation activities are categorized as *local innovation* activities (a = 0.574), while after 1990, 34% are categorized as *local innovation* activities ($a + a_d$ = 0.339). The optimal parameter value a_d = -0.235 suggests a globalization of rare earth catalyst innovation activities following the internationalization of supply chain and production activities. However, using the shares of *local* and *global innovation* activities as weights, the weighted average conditional probability of citing local (US) knowledge is 0.519 before 1990 and then decreases to 0.336 after 1990. This is inconsistent with our previous regression results in *Model 1b* shown in Table 5 for rare earth catalyst technology, which suggested that after 1990 US innovation activities, similar to innovation activities located abroad, utilized more US knowledge through the coefficient for *d* (0.24, $p < 0.05$).

Since our model results for rare earth catalysts do not confirm the regression results, this suggests the alternative explanation of heterogeneity for the observations of the regression analysis. While our current specification of the model restricts the nature of innovation processes to remain constant before and after 1990, industry accounts previously described in Section 2.2 suggest that the locations of rare earth catalyst innovation activities are also influenced by leading customer and national environmental policies and have moved towards a more modular innovation production function. New catalysts are developed autonomously from customer architectures easily replacing older catalysts without impacting system design. Therefore, local knowledge spillovers throughout the supply chain are playing a less prevailing role in the development of new knowledge. Furthermore, as discussed in Section 2.2 the specialization of rare earth catalyst knowledge enables individuals involved in innovation activities to more easily monitor and absorb similarly specialized knowledge generated abroad. This is evident by the dominance of multinational corporations in rare earth catalysts, which maintain production and research and development facilities worldwide.

To test this alternative explanation, we can change our model and remove the restriction that forces the natures of innovation processes to remain the same following the internationalization of supply chain and production activities. We empirically estimate this unrestricted model by fitting the data to the model using the parameters $\Theta_t \equiv (a_{j,t}, s_{l,l,t}, s_{l,g,t}, s_{g,l,t}, s_{g,g,t}, w_{j,t})$ before 1990 and $\Theta_{t+1} \equiv (a_{j,t+1}, s_{l,l,t+1}, s_{l,g,t+1}, s_{g,l,t+1}, s_{g,g,t+1}, w_{j,t+1})$ after 1990, separately. By allowing the nature of rare earth catalyst innovation processes before 1990 to be different than after 1990, we expect to obtain results that are consistent with the key regression result, thus lending force to this alternative explanation of the data.

The results for the direct estimation of our unrestricted model parameters for rare earth catalyst technology innovation activities are shown in

Table 10. Following the interpretation procedure previously described, we find that the weighted average conditional probability of citing local (US) knowledge is 0.254 before 1990 and *increases* to 0.523 after 1990. This result agrees with our regression results, both suggesting that after 1990 US rare earth catalyst innovation activities are more likely to cite available US knowledge. According to the model results, the conditional probability of citing available US knowledge for *local innovation* activities was 0.902 before 1990 and 0.776 after 1990, suggesting that these innovation activities utilize more global knowledge following the internationalization of rare earth supply chain and production activities . Meanwhile, for *global innovation* activities the conditional probability of citing available US knowledge was 0.009 and 0.341 before and after 1990, respectively. This suggests that for innovation activities categorized as *global* local US knowledge become more important. Unlike the results of the restricted model, the unrestricted model suggests that there is an increase in the share of *local innovation* activities after 1990 (a_t = 0.275 and a_{t+1} = 0.419).

Table 10 Catalyst unrestricted model parameters

		Before 1990	After 1990
A	Share of local innovations	0.275	0.419
$s_{l,l}$	Probability a local innovation cites an available Local patent	0.087	0.28
$s_{l,g}$	Probability a global innovation cites an available Global patent	1.2e-4	0.006
$s_{g,l}$	Probability a local innovation cites an available Global patent	0.009	0.008
$s_{g,g}$	Probability a global innovation cites an available Global patent	0.013	0.012
w	Probability of citing within technology patents	0.473	0.670
p_t	Share of US innovations before 1990	0.577	0.452
ESS	Estimated sum of squares	4959.597	8054.924
RSS	Residual sum of squares	3901.648	11995.209
r^2	Coefficient of Determination	0.560	0.402

By modeling the natures of innovation processes for rare earth catalyst and magnet technology development, we have found that knowledge spillovers can play an important role in what innovation stays and what innovation moves away from a home country in response to the internationalization of supply chain and production activities. But we have also found that in certain technologies, the changing nature of innovation activities such as the fragmentation or modularization of the innovation production function can mitigate the importance of geographic proximity and local knowledge spillovers. In these cases, it is critical to recognize alternative innovation drivers such as leading regulators and policy makers.

6 Conclusions

This research shows that trends in the location of innovation activities for two industries, rare earth magnets and catalysts, exposed to the internationalization of supply chain and production activities are different. We find that rare earth magnet innovation is moving away from the US while for rare earth catalysts innovation is remaining in the US. Using direct industry observations and patent data, our regression and modeling results suggest that if knowledge spillovers among segments of an industry supply chain are important and significant supply chain and production activities are relocated, then the location of R&D activities are likely to follow the internationalization of the supply chain. Furthermore, if most innovations are reliant on local knowledge spillovers and innovation increases outside of the home country then some innovation highly dependent on knowledge contained within the home country such as niche applications will stay while other innovation activities will move to access critical knowledge now being produced elsewhere. Yet, as noted in rare earth catalyst innovation, technology characteristics as well as national policies can also drive leading technology developments to continue to be located in a region, even when the supply chain relocates elsewhere.

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 this 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 country and what innovation activities will move outside of the home country. These conclusions complement and extend emerging research which focuses 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) advanced that tasks involving codifiable information can be easily offshored while tasks dependent on tacit information will remain in the US, regardless of their skill level. Similarly, Levy and Murnane (2004), discuss how 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. Our own research suggests that knowledge spillovers across an industry supply chain may be a critical determinant of what activities, including higher value added activities such as R&D, are ultimately offshored rather than the skill or technology level of certain activities.

This question is critical because offshoring has the ability to impact innovation dynamics at the country level as well as policy. 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. In such case, 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 local technology environment matters.

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 of losing innovation capacity that are associated with offshoring. However, it is reasonable to expect that other criteria influencing offshoring decisions may produce confounding risks and benefits to innovation. Therefore, it is also crucial for subsequent research to further explore this issue in more detail.

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