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TECHNOLOGY SHOCKS, TECHNOLOGICAL COLLABORATION, AND INNOVATION OUTCOMES

Melissa Schilling
New York University.
Stern School of Business,
mschilli@stern.nyu.edu

Abstract

A major technology shock can have a profound effect on numerous economic activities and outcomes. A technology shock may simultaneously unleash significant innovation opportunities, while creating great uncertainty in the economic environment. Though it is well-known that firms often use alliances both to respond to uncertainty and facilitate innovation, little is known about how technology shocks affect the collaboration behavior of firms, and how these two factors separately influence innovation outcomes. I integrate an inductive study of a technology shock and concomitant collaboration activity with existing research on alliances and networks to build a set of arguments about how technology shocks will influence alliance behavior, how changes in alliance behavior will influence the global technology collaboration network, and about how each of these changes is likely to influence the innovative outcomes of firms. I test these arguments using large sample panel studies of alliance formation and patenting by US firms. The results suggest that the rise of the internet created a technology shock that subsequently impacted innovation. This shock also led to the crystallization of a giant collaboration network that had innovative consequences of its own.

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Melissa A. Schilling
Stern School of Business
New York University
40 West 4th Street
New York, NY 10012
mschilli@stern.nyu.edu
212-998-0249

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Abstract

A major technology shock can have a profound effect on numerous economic activities and outcomes. A technology shock may simultaneously unleash significant innovation opportunities, while creating great uncertainty in the economic environment. Though it is well-known that firms often use alliances both to respond to uncertainty and facilitate innovation, little is known about how technology shocks affect the collaboration behavior of firms, and how these two factors separately influence innovation outcomes. I integrate an inductive study of a technology shock and concomitant collaboration activity with existing research on alliances and networks to build a set of arguments about how technology shocks will influence alliance behavior, how changes in alliance behavior will influence the global technology collaboration network, and about how each of these changes is likely to influence the innovative outcomes of firms. I test these arguments using large sample panel studies of alliance formation and patenting by US firms. The results suggest that the rise of the internet created a technology shock that subsequently impacted innovation. This shock also led to the crystallization of a giant collaboration network that had innovative consequences of its own.

Technological progress is not always a gradual and incremental process – sometimes there are large-scale discontinuous changes that radically alter production methods and outputs in an industry, or in the economy as a whole. Such a technology shock can occur in many different ways. For example, it may be the result of advances in science that enable new trajectories of innovation (Dosi, 1982). It may also result when an existing technological alternative improves to a point that it overtakes the dominant design (Christensen, 1999), or is transplanted to a new domain (Levinthal, 1998). It can also occur as the result of a shock in another system, such as when a change in input prices dramatically changes the price/performance relationship for a technology (Ehrnberg, 1995), or when a change in the regulatory environment significantly alters the technologies permitted (or demanded) in the market. There is a rich history of research in economics on technology shocks that has shown that such technology shocks can have a significant effect on investment, economic growth and labor productivity (e.g., Alexopolous, 2011; Christiano & Eichenbaum, 2003; Gali, 1999).

The most visible technology shocks are those in "general purpose technologies," i.e., technologies that have relevance well beyond a single industry such as those in engines, telephony, the transistor, etc. General purpose technology shocks can create significant uncertainty and economic churn in the form of new firm entries, exits, and mergers as capital is reallocated across organizations with different capabilities (Jovanovic & Rousseau, 2005). [1] As Levinthal (1998) notes, a major technology shock creates new selection pressures in the environment, and thus can induce major shifts in industrial configurations, much the same as punctuated equilibrium models explain eras of major change in biological species.

One of the ways firms respond to the tremendous uncertainty and opportunity of a technology shock is through the formation of alliances (Anand, Oriani, & Vassolo, 2010; Rosenkopf & Padula, 2008). Alliances help firms to resolve uncertainty through exchanging resources, and cooperating to influence evolving standards (Eisenhardt & Schoonhoven, 1996; Hoffman, 2007; Pfeffer & Salancik, 1978; Powell et al., 2005; Rothaermel, 2001). Alliances also help firms to innovate more quickly or effectively by pooling their resources and sharing risk (Grant & Baden-Fuller, 2004; Hagedoorn, 1993; Madhavan, Koka & Prescott, 1998; Schilling & Steensma, 2001; Stuart, 1998). There may be a period of intense ferment in which there is exploration of (and competition between) alternative designs (Tushman & Anderson, 1986). Firms will thus actively seek to acquire information about the prospects for alternative

[1] Other types of shocks can also induce intense uncertainty. For instance, significant regulatory reforms or other changes in the institutional environment can introduce many new opportunities or challenges that may prompt new firms to appear, and existing firms to reorganize their business models or their relationships with other organizations (Corrado & Zollo, 2006). Similarly, an economic shock, such as a sudden financial recession or rapid changes in exchange rates, can lead to a significant reshuffling of who the "winning" and "losing" firms are.

designs. A technological shock may also result in significant revision of existing business models and value chains, and the end configuration may be far from obvious in early stages of the shock. Firms may thus respond to a shock by using alliances to place "options" on multiple potential pathways for the future (Vassolo, Anand, & Folta, 2004).

This suggests that firms might respond to a technology shock by increasing their degree of alliance activity, or changing the types of partners they choose, both of which would influence the structure of the overall collaboration network.[2] As graph theory has shown, an increase in the number of links among a set of nodes can result in a non-linear increase in connectivity among those nodes known as a "phase transition." A set of disconnected clusters may suddenly transform into a single large web (Kauffman, 1993). This suggests that if a technology shock causes firms to significantly increase their alliance activity, it may help to cause a much larger web of connected firms to crystalize. A related line of work has shown that the introduction of atypical links into an otherwise sparse and "orderly" network can result in a radical drop in the average path length of the network (Watts & Strogatz, 1998). The atypical links create shortcuts in the network that significantly contract the distance between connected nodes. If a technology shock causes organizations to seek out different types of partners than those they would normally choose, these new links may similarly create shortcuts in the global collaboration network, dramatically changing the connectivity between connected members. In sum, there are strong reasons to suspect a technology shock could induce dramatic changes in the global collaboration network, though due to data limitations, this was nearly impossible to investigate empirically until very recently.

Furthermore, since the web of collaborative relationships that connects organizations can act as a conduit for information and other resources, a technology shock that significantly influences the size or structure of that web might also influence innovation via this indirect pathway (e.g., Ahuja, 2000; Schilling & Phelps, 2007). That is, technology shocks might have a direct effect on innovation by creating new innovation opportunities, a direct effect on alliance activity and networks, and an indirect effect on innovation as mediated by alliances and networks.

Though various strands of research have provided evidence of pieces of this dynamic process, data limitations have hitherto prevented looking at these pieces together. It is only very recently that researchers have had access to large scale alliance datasets and network tools that permit analyzing

[2] While a considerable body of research on inter-firm networks has demonstrated the endogeneity and inertia of network structure, other recent studies have documented the impact an exogenous shock can have on network structure (Glassmeier, 1991; Madhavan, Koka, & Prescott, 1998; Rosenkopf & Padula, 2008; Spedale, 2003).

longitudinal changes in overall collaboration networks, which may then be compared to patterns of innovation outcomes. However, examining the pieces individually only permits us to speculate about the whole. Just as the proverbial blind man may come to erroneous conclusions about an elephant if he only touches its tail, we cannot really understand the direct and indirect effects of a technology shock on collaborative behavior and innovative outcomes by reading strands of literature that have tackled each piece in turn (and notably, there is still very little evidence linking overall collaborative network structure with innovation outcomes). I thus analyze the following questions here: Do firms significantly increase their alliance activity in response to a technology shock? Does a technology shock affect the types of partners firms choose? How do these responses affect the overall collaboration networks that structure the flow of information and resources among connected firms? And do changes in the collaboration network lead to economic outcomes above and beyond those created by the underlying technology shock? The last question here is perhaps the most important: unless we can disentangle the direct effect of the technology shock on innovation from the effect that is mediated through collaborative activity, we will not really understand the effect of technology shocks and collaborative activity on innovation.

I examine here how a major technology shock affected the alliance activity of organizations worldwide, and how these changes in alliance activity affected the global technology collaboration network. I also examine whether the shock and the resulting collaboration activities were related to subsequent innovation outcomes. I first use inductive research to explore the patterns in worldwide technological collaboration activity around the time of a recent major technology shock: the rise of the internet. I then integrate this research with existing theory on alliances and networks to develop arguments about a) why technology alliances are likely to be one of the first ways that firms will respond to a technology shock, b) how a shock is likely to affect both the quantity of collaboration activity and the types of partners chosen, c) how the changes in alliance activity will affect the overall collaboration network, and d) how the shock, the alliance activity, and the collaboration network are likely to affect subsequent innovation outcomes. I then test these arguments using large sample panel studies of industry-level alliance patterns and firm-level collaboration and patenting behavior.

THE INTERNET SHOCK AND CHANGES IN COLLABORATIVE ACTIVITY

In 1969 the U.S. Department of Defense commissioned the ARPANET program (Advanced Research Projects Agency Network Program) to research computer networking, and established the first four nodes (at UCLA, Stanford, UC Santa Barbara, and U. of Utah) of what would later be termed the “internet.” By 1971 there were fifteen nodes, and in the same year Ray Tomlinson invented an email program that became an immediate hit. Throughout the 1970s the network was expanded and new protocols were developed to make communication via the network more efficient. Though there was considerable growth in the internet throughout the late 1970s and the 1980s, through most of this timeframe it was still primarily a tool of science and education -- its reliance on text-based programs limited its commercial appeal. This was exacerbated by the fact that commercial use of the ARPANET backbone was forbidden.

By the early 1990s, however, the network began to grow beyond the constraints of the original ARPANET backbone; other government institutions and commercial providers had built their own backbones and regional network access points had become the primary interconnections between networks, ending any limitations on commercial use. Suddenly the internet began to attract the widespread attention of business and media. The number of internet hosts and the number of people using the internet began to grow explosively (see Figure 1). The 1993 launch of Mosaic, a graphic interface for the internet helped to fuel the frenzy of business activity that was directed at leveraging what was now called the World Wide Web. At the same time, rapid advancements in semiconductors, networking hardware, and software enabled dramatic increases in the capacity and speed of the internet (Mowery and Simcoe, 2002).[3]

There are numerous studies that have identified the rapid growth of the internet in the early 1990s as a technology shock (e.g., Alexopoulos, 2011; Arnold, 2003; Lyytinen & Rose, 2003). As shown in Figure 1, the early 1990s were pivotal turning points for the internet. In 1993, internet penetration of the U.S. market surpassed three percent, moving from the "innovator" segment of the market to the "early adopter" segment of the market (Rogers 1995), and the number of internet hosts was rising exponentially. The sea change that was underway is illustrated by the stark contrast in the following quotes, only two years apart:

"*Let's face it. Not many members of the public -- even the computer literate public - are on the Internet*" (John Goodwin, Email 101, a tutorial for the internet, in July of 1993).

"*Businesses and entrepreneurs are rushing into cyberspace like forty-niners driven mad by gold fever*" (Vic Sussman and Kenan Pollack, *U.S. News and World Reports*, November of 1995).

----------------------------Insert Figure 1 About Here----------------------------

The rise of the internet coincided with rapid innovation in related networking equipment and software, and precipitous drops in prices of information technology products like semiconductors and telecommunications equipment. These interdependent processes collectively caused a major shock to the economy (Jorgenson, 2001). The epicenter of this shock was in the information technology industries, but its reverberations were felt in many industries, and in many layers of the economy. The internet was a

[3] Please see Mowery & Simcoe (2002) for a more complete discussion of the history of the internet.

"general purpose technology" with the potential to transform information dissemination on a massive scale (Mowery and Simcoe, 2002), creating tremendous uncertainty for organizations.

Like most gold rushes, the number of people and firms that would ultimately strike it rich was a small portion of those who flooded into the market. By late 2000, a large number of dot-com companies had burnt through their venture capital or equity raised through initial public offerings, and they began to fail. Information technology stock indices went into sharp decline. Most had stabilized by 2004 at a level far lower than the 2000 peak. The world had, however, entered a new era of information access and distribution.

A Spike in Alliance Activity

The early 1990s also witnessed a dramatic surge in technology alliance activity, including R&D alliances, joint ventures, cross-licensing, and cross-technology transfer agreements (Figure 2). According to data available through Thomson Financial's SDC database, the number of publicly-announced technology alliances formed per year grew roughly 300% from 1990 to 1995, and then subsequently declined just as sharply, stabilizing at levels close to those in 1990 by 2002.

------------------------Insert Figure 2 About Here ------------------------------

Though we might first suspect that this spike could be a result of a change in practice at SDC, we can eliminate that possibility by comparing the trend in alliances across multiple databases. Figure 3 provides a set of charts showing the standardized alliance counts over time from the SDC database, the CORE database of joint research ventures filed under the National Cooperative Research Act, and the MERIT-CATI database that is maintained by Maastricht University in the Netherlands (SDC and MERIT-CATI are shown only for 1990 forward as they are considered more reliable after this time point; the MERIT-CATI data was available only through 2003).[4] This chart shows strong agreement about the peak in alliance activity in 1995, and the standardization of the values further reveals that the datasets have high agreement about the relative magnitude of the peak in comparison to the overall variance in alliance announcements over the 1985-2005 time period If these data sets were treated as multiple items of a single measure of alliance activity, the combined measure would have a coefficient alpha of .83, and thus would be considered very reliable (Nunnally, 1978).[5]

----------------------------Insert Figure 3 About Here ------------------------------

[4] Because the MERIT-CATI database has a very heavy focus on biotech alliances which distorts the temporal patterns, the biotech alliances are omitted from the MERIT-CATI data shown here.

[5] For a more complete analysis of the consistency in temporal patterns across multiple alliance datasets, please see Schilling, 2009.

While it is well established that most alliance databases are incomplete, and are at best samples, it is important to note that the CORE database contains the entire population of joint research and technology alliances formed under the National Cooperative Research Act. Its correlation with the other databases thus provides some reassurance that the spike in reported alliances was a real spike in alliance *activity*, and not just a trend toward increased *reporting* of alliances.

A sector breakdown of the alliance activity indicates that of the five sectors that appear to contribute most significantly to the mid-1990s peak, four are central to information technology: Electronics and electrical equipment (which includes both semiconductors and telecommunications equipment); business services (which is heavily dominated by software); industrial machinery (which includes computers); and communications services (see Figure 4).[6] A count of the alliances by *primary activity* (based on SDC's classification of alliance activities into SIC codes) reinforces the prominence of information technology during the alliance spike. The percentage of alliances that were formed primarily for information technology activities (computer equipment 3571-3577; communication equipment 3661-3669, semiconductors and related components 3671-3679, communication services 4812-4899, software 7371-7379) rose from 26% in 1990 to a peak of 58% in 1995, then dropped sharply. The graph also indicates, however, that the surge in alliance activity extended well beyond the IT sectors – a point I will return to later.

----------------------------Insert Figure 4 About Here---------------------------------

Though there were a number of exciting information technology developments in the early 1990s (e.g., increasing use of mobile phones, continued growth in personal computer sales), we can isolate the effect of the internet and concomitant networking technology by analyzing the deal text of the alliances. Figure 5 shows the percent of alliances where the deal text specifically mentions "cellular phone" or "mobile phone", "personal computer" or " PC ", "internet", or "network." The differences in these percentages are striking; a much larger percentage of the deals cite "internet" or "network" in the deal text than the other terms. Furthermore, there is a clear spike in use of the terms "internet" and "network" in the mid-1990s that corresponds to the spike in the overall use of alliances. Figure 6 provides further evidence, by showing that there is a remarkable correspondence between the IT alliance data[7] and a) the yearly growth rate of internet hosts, and b) the multifactor productivity growth for the semiconductor industry (whose

[6] Two other sectors that standout during this time period are chemicals (primarily pharmaceutical and biotech alliances), and engineering and management services (which is dominated by management consulting and biological research services).
[7] An average was created of the standardized number of IT alliances as reported by SDC, CORE, and MERIT-CATI.

advances were primarily responsible for the rise of both the internet and personal computers).[8] The correlation between the number of IT alliances and growth in internet hosts is .70 ($p<.01$), and the correlation between the number of IT alliances and semiconductor multifactor productivity growth is .72 ($p<.01$). The standardized items collectively achieve a Chronbach's alpha of .82, suggesting that the three series (IT alliances, growth rate of semiconductor multifactor productivity, growth rate of internet hosts) could be considered multiple measures of the same underlying construct.

------------------------Insert Figures 5 & 6 About Here--------------------------------

Figure 7 shows a graph of the IT alliance data shown previously along with other indicators of activity in the IT sector: The number of public computer hardware and software firms, acquisitions of US IT firms, R&D spend and sales by publicly-held computer hardware and software firms, the market capitalization high of computer hardware and software firms, patents with "internet" in the abstract (by application date), and Wall Street Journal articles that include the word "internet." All of the series are standardized to permit showing them on the same graph. Notably, the alliance data show the first spike in activity, hitting their peak in 1995. The next series to show a major upsurge are the number of publicly-held computer hardware and software firms. The number of patent applications (that were subsequently granted) with the term "internet" in the abstract, the market capitalization high of computer hardware and software firms, acquisitions of US IT firms, and the number of Wall Street Journal articles that mention the "internet" are all extremely highly correlated, and hit a sharp peak in 2000 -- this is the information technology "bubble" that the general public would have been aware of. By contrast, to the preceding series, the data on R&D spend and sales march upward more gradually, and are also very correlated. This highlights a serious limitation in using measures based on R&D intensity to identify a shock in technological opportunity: R&D budgets are constrained, often a fixed percent of sales, and thus are relatively inelastic despite shocks in the environment. Though R&D does indeed turn up after the shock, the change in its trajectory is quite gradual in comparison to the change in alliance activity. Overall, the patterns in the graph suggest that alliances are one of the first ways that firms will respond to a shock in technological opportunity or uncertainty; the internalization of innovation activities takes much longer. Furthermore, the data suggest that alliances are a much earlier indicator of the technological shock than more commonly monitored indicators such as sales, R&D, and market capitalization.

-------------------------------Insert Figure 7 About Here------------------------------

As noted previously, though the information technology industries disproportionately account for the spike in alliance activity, other industries also exhibit a surge during this time period. This should not be

[8] Multifactor productivity growth, otherwise known as the Solow residual, refers to growth in output that cannot be accounted for entirely by growth in labor and capital inputs. This measure is widely used in economics to capture technological change (Solow, 1957; Terleckyj, 1980).

surprising -- the technological shock of the internet created a wave of uncertainty and opportunity that rippled through many industries. There was significant uncertainty in how the internet and associated networking technologies would transform an industry's business models. It would disintermediate some value chains while creating new intermediaries in others. It would enable major changes in how organizations communicated both internally and externally with customers and suppliers. The net result would be significant industry churn that could cause once dominant organizations to be displaced by competitors that made better gambles about how to exploit the new technologies. To deal with all of this uncertainty, firms not only formed more alliances, but also reached out beyond their typical alliance partners. In particular, many organizations sought to form relationships with information technology firms in order to access information and capabilities that would help them respond to – and benefit from – the rapid advances in networking technologies. As shown in Figure 8, firms in both IT and non-IT industries forged a larger percent of their alliances with IT firms during the mid-1990s period.

-----------------------------Insert Figure 8 About here----------------------------

Overall, the data suggest that rapid innovation in the internet and related information technologies during the early 1990s may have dramatically influenced alliance behavior. Alliances serve at least four main functions in helping firms to respond to a turbulent environment. First, under conditions of great uncertainty firms may use alliances as a sensemaking activity that enables them to probe the knowledge of other firms and develop shared interpretations of the changes unfolding in their environment (Hoffman, 2007; Mitchell & Singh, 1992). This is highly symmetric with arguments made in the sociology literature about how individuals use their social networks to respond to turbulence in their lives (Pescosolido, 1992; Srivastava, 2012).

Second, alliances enable firms to more quickly or effectively respond to the shock by accessing the resources and capabilities of others. Alliances, like other communication and collaboration devices, enable firms to pool their resources. Whereas R&D budgets tend to be constrained (and often a fixed percentage of sales), alliances are often considered to be a flexible, low-cost, and fast way to pursue solutions to a technological problem. Alliances enable firms to share the costs and risks of new technological ventures, and can enable firms to combine complementary technological skills to more rapidly achieve desired outcomes.

Third, firms can use alliances to build coalitions to shape the evolution of the organizational environment, thus actively influencing the outcome of the uncertain phase. Through alliances firms can create, and build support for, shared standards (Schilling, 2002). By agreeing to particular standards, allied firms work to resolve some of the uncertainty in the technological trajectory, thereby reducing some of the risk of their investment in the technology. By actively shaping the technology trajectory, firms can improve the likelihood of the industry selecting a dominant design that best leverages their own technological capabilities or positioning. The process of determining shared standards also helps firms to negotiate how value will be allocated across the various players.

Fourth, alliances are an important mechanism for building legitimacy at both the individual firm level, and at the collective standard level. For example, Stuart (2000) notes that young or small firms may use alliances with larger more technologically prominent firms as organizational endorsements that help build confidence in the young or small firm's capabilities, thereby improving its access to customers and other partners. Similarly, the credibility or power of the organizations that back a particular standard can dramatically affect its likelihood of winning a standards battle. The coalitions that emerged around Toshiba's HD-DVD and Sony's Blu-Ray video standards aptly illustrate this. In early 2008, Toshiba had lined up several major Hollywood studios for its format, including Time Warner's Warner Brothers, Viacom's Paramount Pictures and Dreamworks Animation, and NBC Universal's Universal Pictures. Sony had its own Sony Pictures Entertainment, Disney, News Corporation's 20th Century Fox, and Lions Gate Entertainment. However, on the eve of the Consumer Electronics Show in Las Vegas in early January 2008, Time Warner announced it would be defecting to the Blu-ray standard. The loss of this powerful ally set off a chain reaction among retailers, leading to Best Buy, Wal-Mart, and Netflix all announcing that they would exclusively stock Blu-ray DVDs. The blow was unexpected—and devastating—for Toshiba, which publicly conceded defeat the following month (Hall, 2008).

The preceding suggests that that we would expect a technology shock to result in increased alliance activity:

> **Hypothesis 1**: A technology shock will lead to increased alliance activity (e.g., more forms forming alliances, firms forming more alliances on average, or both).

The data also indicated that the rise of the internet did not just influence alliance activity in the IT industries; its effects were felt through a wide range of industries. Many non-IT firms formed alliances with IT firms or for IT specific projects. During periods of stable competition, firms are likely to form alliances with suppliers, complementors, and would-be competitors, as these are the organizations that are most likely to possess the relevant information needed by the firm, or be the source of the most important interdependencies the firm needs to manage. Previous work has emphasized the self-reinforcing nature of alliance networks due to the benefits of learning through repeated partnerships and referrals from common third parties (Uzzi 1997; Gulati and Gargiulo 1999; Anand and Khanna 2000; Goerzen 2007), leading organizational fields to become well defined. However, when solutions are needed to a fundamentally new kind of problem, the repository of knowledge within the existing network about both solutions and prospective partners may be inadequate, leading firms to seek out new kinds of partners (Madhavan, Koka, & Prescott, 1998; Rosenkopf & Padula, 2008). Firms might seek relationships with firms that appear more central to (or knowledgeable about) the new technology, blurring the boundaries of traditional organizational fields. More generally, when a shock in technological opportunity occurs in a general-purpose technology, we may expect to see more diversity of alliance partners, and more alliances formed with organizations that are in industries that are close to the center of the technology shock.

> **Hypothesis 2**: A general purpose technology shock will lead to firms increasing the diversity of their alliance partners.
>
> **Hypothesis 3**: A general purpose technology shock will lead firms to form more alliances with firms that are in industries that are close to the technology in which the shock originates.

The combination of an increase in overall alliance activity, and the greater use of cross-industry collaborations, is likely to have a dramatic impact on the overall global technology collaboration network, as discussed – and empirically explored -- in the next section.

The Global Technology Collaboration Network

As firms forge these collaborative relationships, they weave a network of paths between them that can act as conduits for information and other resources. These networks may initially be sparse or fragmented, but an increase in either the number or diversity of alliances (or both) can dramatically increase the connectivity of such networks. The importance of the number of links among a given set of nodes (or *density*) was first shown with random graphs. If, for example, one starts with a set of disconnected nodes and adds links one at a time between randomly chosen pairs of nodes, initially most nodes will be isolated, and a few nodes will be connected to one or two others. As the ratio of nodes to links approaches .5, many of these small clusters will start to be connected to other small clusters, causing the size of connected components to increase and the number of individual clusters to decrease. As the ratio of links to nodes increases past .5, a single giant component connecting most of the nodes will suddenly crystalize (Bollobàs, 1985; Erdos & Renyi, 1959) – this is known as a phase transition. Phase transitions are a natural property of random graphs (Kauffman, 1993). Alliance networks, however, are not random. Instead, the patterns of alliance formation tend to be highly clustered because firms are more likely to form relationships with other firms with which they share some type of proximity or similarity, such as geography or technology (Baum et al. 2003; Rosenkopf & Almeida, 2003). It is here, however, that the role of diverse or atypical alliances come into play. As shown by Watts and Strogatz (1998), in graphs that are sparse and non-random (e.g., highly clustered), a relatively small portion of random or atypical links can lead to a sharp decrease in the average path length between connected nodes, enabling even a highly clustered network to have an average path length close to that of a random graph with the same number of nodes and links.[9] This process underlies the "small world". The preceding suggests that an increase in either the degree of alliance formation, or the diversity of alliance formation, could greatly increase the likelihood of a phase transition that causes a giant component of connected firms to emerge.

To empirically examine this possibility, I construct the global technology collaboration network using announcements of technological collaboration agreements drawn from Securities Data Corporation's Joint Venture and Alliance database. I included every publicly-announced technology collaboration agreement (joint R&D agreements, cross-licensing agreements, and cross-technology transfer agreements) reported as *completed*[10] between any two or more organizations (including firms, non-profits, government agencies, universities, etc.), from anywhere in the world.[11] Notably, relying on this data source limits my analysis to only formally-announced relationships, and likely understates the connectivity of the network that would exist if I were able to incorporate informal collaboration relationships. However, there is a strong correlation between the pattern of formal and information relationships between firms, as informal arrangements often lead to the types of formal agreements that I observe here (Powell, Koput and Smith-Doerr 1996; Rosenkopf, Metiu and George 2001). The data were gathered for the period 1990 to 2005 (inclusive). I chose 1990 as the initial year because information on alliances formed prior to 1990 is very sparse in the SDC database (Anand and Khanna 2000: 300; Schilling 2009). The resulting dataset includes 13,304 total alliances between 13,906 organizations from 105 nations.

Alliances typically last for more than one year, but alliance termination dates are rarely reported. This requires the researcher to make an assumption about alliance duration. Previous research has typically used windows ranging from one to five years (e.g., Gulati and Gargiulo 1999; Stuart 2000). I have used

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[9] This process underlies the "small world" phenomenon whereby most individuals are connected via a surprisingly short path of acquaintances.

[10] SDC reports both *pending* and *completed* announcements; I utilize only those alliances reported as completed here.

[11] Though it is often assumed that the SDC has a heavy bias toward US-based firms, recent research suggests that such an assumption may be unwarranted. In a comparative analysis of the geographic scope of the SDC alliance database versus the MERIT-CATI database (Schilling, 2009), it was found that both datasets report more U.S. participants than participants from any other country, and for both datasets the aggregate for North America is over 1.5 times the aggregate for the next highest region, Europe. The main difference in geographic coverage across the two datasets was that SDC has far more participants reported that are from non-OECD countries (21.48% in SDC versus 3.38% in MERIT-CATI). The non-OECD participants in the SDC database are overwhelmingly Asian, with the leading countries being China, Malaysia, Singapore, Hong Kong, India and Thailand, in that order, and collectively accounting for 17.28% of the country-participant counts.

one-year alliance windows for the graphical pictures of the alliance networks here as three-year windows obscure some of the temporal changes, however three-year windows are used for the panel analysis study described later, and graphical snapshots based on three-year windows (i.e. 1990-1992, 1991-1993, …1995-1997), are available from the author upon request. Each network snapshot was constructed as an undirected binary adjacency matrix (Wasserman and Faust 1994). [12] The technological collaborations are considered to be bi-directional relationships, resulting in an undirected graph. Multiple alliances between the same pair of firms in a time window are treated as one link.

Ucinet 6.2, a leading social network analysis software package, was used to obtain measures of the structural properties of each of these networks (Borgatti, Everett and Freeman 2002). NetDraw 2.24 was used to generate pictures of the networks (Borgatti, Everett and Freeman 2002). The "spring embedding" feature was used in NetDraw to better visualize how close or far each organization is from the others in the network. This algorithm locates nodes closer to each other if there is a short path length between them, and locates nodes farther from each other if the shortest path between them is long, or if there is no path between them at all.[13] A "node repulsion" feature helps to reduce the likelihood of nodes being located on top of each other, and an "equal path length" feature helps to ensure that the distances between adjacent nodes are commensurate. If a network has one large "component" (a group of nodes that are all connected together) and many pairs or triples of nodes that are not connected to this large component, the algorithm often (but not always) results in the pairs and triples being grouped into a single mass that is separate from the large component. For example, in most of the network snapshots here, there is a single large component that wraps around the graph space, and the pairs and triples that are not connected to this large component form a lima bean-shaped mass in the center of the graph. When there are multiple large components, or a single large component that has several distinct lobes, the pairs and triples not connected to these components may be pushed out into a ring around the large component(s), or may not exhibit any discernible organization.

[12] A binary adjacency matrix is a square matrix with nodes (e.g., organizations) as rows and columns. The entries in the adjacency matrix, x_{ij}, indicate which pairs of nodes are adjacent (i.e., have a relationship). In a binary matrix, a value of 1 indicates the presence of a relationship between nodes *i* and *j*, while a 0 indicates no relationship.

[13] The path length between nodes refers to the shortest path between them based on links between them and their partners. For instance, if A is partnered with both B and C, but B and C are not partnered with each other (and have no other partners, the path length between A and B is one, the path length between A and C is one, and the path length between B and C is two (B → A →C).

Table 1 provides some statistics for the yearly network snapshots, and Figure 9 provides graphical pictures. First it is important to make a few observations about the network statistics.
As shown, the average number of organizations that formed at least one technology alliance per year as reported by SDC from 1990 to 2005 was 1279. The data indicates, however, that there was considerable variation in the number of participants for each year, ranging from 452 in 2004 to 3,176 in 1995. As indicated in Table 1, for many of the years a large percentage of the firms participating in technology collaboration agreements were connected into a single large component, reaching a high of 46% in the 1992 snapshot. However, the number of alliances dropped precipitously toward the end of the decade, fragmenting the network into many smaller components – in the years 2001-2005, less than 5% of the organizations reported to have technology alliances were connected to the largest component based on yearly snapshots. A similar pattern is observed if three-year alliance windows are used to create the networks – in this case, the percentage of organizations connected to the largest component reaches 58% in the mid 1990's, and drops to an average of 9% for 2001-2004.

--------------------Insert Table 1 and Figure 9 About Here--------------------------

Graphical pictures of the network snapshots provide further insight. The graphs are color coded by component so that the nodes connected to the largest component are discernible from the other nodes (the largest component is red in color copies of the article, and appear dark gray in black and white copies of the article). These graphs provide a stark visualization of how the dramatic rise and fall of alliance activity in the mid- 1990s impacted the overall connectivity of the technology collaboration network. As shown, in the snapshots leading up to the mid-1990s, the main component grows very large and dense. After the alliance spike, the main component begins to thin, and by 1998 the main component has fragmented into many smaller components. As noted early in the paper, the response of firms to a technological shock is much like that of miners to a gold rush: Initial excitement may drive a frenzied initial response that is unsustainable, and only a portion of those who rush in will harvest significant value. It is costly to forge and sustain alliances. Such agreements can also put firms at risk of having their proprietary technologies expropriated by others. This puts significant constraints on the number of collaboration agreements that firms can sustain. As a result, a rapid increase in alliance activity is, in general, likely to be followed by a subsequent significant decrease in new alliance formations that returns overall alliance activity to an equilibrium level that is lower than the peak (though it need not match the level prior to the sudden increase, as some types of shocks create lasting changes in the cost and opportunity structure of alliance activity). In the case of a technological shock, much of the uncertainty will typically be resolved over time as standards emerge and firms gain a sense of how they should (or should not) respond. Furthermore, over time, firms will be able to replace or supplement their alliance activity with other responses to technological change, such as redirecting their in-house R&D portfolios, hiring and developing employees with needed capabilities, or merging with other firms. These activities take longer to deploy, but yield more control over the information and capabilities that are acquired.

The preceding suggests that a major technology shock, and in particular a major general purpose technology shock, can lead to a significant (albeit often temporary) increase in the size of the largest component of organizations connected through alliances.

> **Hypothesis 4**: A general purpose technology shock will significantly increase the size and/or density of the largest connected component of a collaboration network.

If we believe that alliance networks are important mediums for the transmission of information and other resources, as has been suggested in recent research (e.g., Gay and Dousset 2005; Robinson and Stuart 2007; Schilling and Phelps 2007), then the rise and fall of this network component might influence innovation outcomes, as discussed in the following section.

Innovation Outcomes

A major technology shock will typically lead to a surge in innovation and patenting by creating new innovation opportunities and strategic imperatives (Kortum & Lerner, 1998) – this point is already well made in the economic and management literatures. However, a technology shock may also indirectly influence innovative outcomes through its influence on alliance formation and the structure of the global collaboration network.

There is significant evidence that alliances are related to innovation outcomes. As noted previously, alliances are an important way that firms can pool their knowledge and other resources to facilitate innovation. Large sample studies have found that alliance relationships facilitate knowledge flows between partners (Gomes-Casseres, Hagedoorn & Jaffe, 2006; Mowery et al. 1996) and enhance the innovative performance of firms (e.g., Deeds & Hill, 1996; Stuart, 2000). Alliances may thus both directly influence innovation, and be an indicator that firms anticipate innovation opportunities. If a technology shock induces greater alliance formation, those alliances may influence innovative outcomes even in ways that are not due to the technology shock itself.

A rapidly growing body of recent research also suggests that the size and structure of technology collaboration networks can significantly influence important outcomes such as knowledge spillovers, innovation rates, initial public offering success, the diffusion of governance practices, and others (e.g., Powell, Koput & Smith-Doerr 1996; Uzzi, 1996; Ahuja 2000; Gulati & Higgins, 2003; Rosenkopf & Almeida, 2003; Gay & Dousset, 2005; Robinson & Stuart, 2007; Schilling & Phelps, 2007; Gilsing et al., 2008). This suggests that if a technology shock significantly influences the size or density of a technology collaboration network, it can set up an endogenous cycle of innovation: A technology shock increases the degree and/or diversity of alliance formation, which creates a larger or more robust collaboration network that creates paths for information and other resources to flow between organizations that would not normally be connected, which in turn results in greater rates and/or greater diversity of subsequent innovation.

These arguments warrant a moment to consider why information would be likely to travel along the paths of an alliance network beyond any individual alliance. Individuals and firms go to great lengths to protect their proprietary information from being transmitted within or beyond a particular collaboration, suggesting that the appropriate level of analysis is the dyad, and the larger network ought not matter very much. It is important to note, however, that much of the information exchanged between individuals and firms is considered nonproprietary and thus is not deliberately protected from diffusion. For example, firms engaged in technological collaboration might freely exchange information about their suppliers, potential directions for future innovation, scientific advances in other fields that are likely to impact the industry, etc. There is considerable evidence, for example, that a firm's alliance partners are a key source of referrals to other potential partners that possess needed technologies, are trustworthy, or possess other desirable qualities (Gulati 1995). Other information exchanged between firms is considered proprietary but is imperfectly protected from diffusion. Even when collaboration agreements have extensive contractual clauses designed to protect the proprietary knowledge possessed by each partner or developed through the collaboration, it is still very difficult to prevent that knowledge from ultimately benefiting other organizations. Secrecy clauses are very difficult to enforce when knowledge is dispersed over a large number of employees or embedded in visible artifacts. Even patenting provides only limited protection for knowledge embedded in technological innovations. In many industries it is relatively simple for competitors to "invent around" the patent (Levin et al., 1987). A rich history of economic research provides further evidence of the positive externalities, known as technological spillovers, created by an organization's research and development efforts (Jaffe, Trajtenberg & Fogarty, 2000), suggesting that information diffuses between organizations whether intended or not, fueling innovation in the broader community. Consistent with this, research has shown that the extent to which a firm is indirectly connected to other firms in an alliance network enhances its innovativeness (Ahuja, 2000; Owen-Smith & Powell, 2004; Schilling & Phelps, 2007; Soh, 2003).

The preceding suggests that there may be (at least) three potential paths by which a technology shock might foster innovation. First, the technological shock may have a direct effect due to the inherent technological opportunities unleashed by the shock. Second, the alliances formed in response to the shock may lead to innovation due to the increased pooling and cross-fertilization of the knowledge and resources of partner firms, partially mediating the effect of the technology shock. Third, the larger or denser overall collaboration network may facilitate the flow of a greater amount and diversity of information between connected firms, partially mediating the direct effect of alliances (Baron & Kenny, 1985) (see Figure 10).

-------------------------------Insert Figure 10 About Here-------------------------------

Hypothesis 5: A technology shock will have a direct positive effect on innovative outcomes.

Hypothesis 6: Alliance formation will have a direct positive effect on innovative outcomes, and partially mediate the positive effect of the technology shock.

Hypothesis 7: A larger or denser overall collaboration network will have a direct positive effect on innovation outcomes, and partially mediate the positive effect of alliance formation.

The graph in Figure 7 already provides some evidence of the direct or indirect effects of the technology shock on innovative outcomes: Patents with the word "internet" in the abstract climb sharply in the years following the spike in the composite measure of internet growth. However, I attempt to disentangle the direct and indirect effects of the technology shock, alliances, and overall collaboration network in the following section.

METHODS

In this section, I first test the arguments regarding a technology shock's effect on alliance activity. I use industry-level measures based on the alliance data above, and a technology shock index that is a composite of the yearly growth rate of the internet and related technologies. Because there are strong reasons to believe that many firms may have increased their formation of alliances with IT firms as a result of the shock, I will assess the relationships between the technology shock variable, the alliance industry diversity undertaken by firms, and the percent of alliances formed with IT industries. I will repeat this analysis also for two subsamples, 1) firms that are in non-IT industries, and 2) firms that are in IT industries.

I then test the arguments about the effect of the technology shock, firm-level alliances, and firms' network reach on subsequent innovation using a large-sample panel study of firm-level patenting rates. I test for the proposed mediating relationship of network reach using the four-step approach outlined by Baron and Kenny (1986): 1) First it is established that the initial variable (proposed mediated variable) is related to the outcome, 2) next the relationship between the initial variable and the proposed mediator is established, 3) then the relationship between the mediator and the dependent variable is assessed, while controlling for the initial variable, and 4) finally, it should be established that the effect of the initial variable on the dependent variable is significantly decreased when controlling for the mediator (or is zero, in the effect of full mediation). I will use the Sobel test to establish the significance of the mediating relationships (MacKinnon, et al, 2002).

Patents provide a measure of novel invention that is externally validated through the patent examination process (Griliches 1990; Griliches, Pakes & Hall 1988). Patent counts have been shown to correlate well with new product introductions and invention counts (Basberg 1987). Trajtenberg (1987) concluded that patents are valid and robust indicators of knowledge creation and innovation.[14]

Since patenting norms and systems vary across regions, I utilize data only on North American firms for this portion of the study. From the set of 13,906 organizations that participated in the global technology collaboration network between 1990 and 2005, I identified all North American publicly-held firms with non-zero sales that participated in at least four of the network snapshot periods, and that apply for at least one patent (that is subsequently granted) during the study period, which yields a set of 409 firms. Restricting the sample to this set ensures that I can obtain reliable financial data on the firms, and that they have variance on the network measure.

Dependent Variables

Alliance industry diversity. I create a measure of the diversity of industries with which organizations form alliances by first calculating a Herfindahl-Hirschman Index (HHI) of the industries with which organizations in the target industry have formed alliances:

$HHI = \Sigma\, p_{ij}^2$

where p_{ij} is the percentage of target industry *i*'s alliances that are formed with partners in industry *j*. The maximum value this measure can take is 10,000 (where all of industry i's alliances are formed with the same industry j – this is most likely to happen when i = j, i.e., organizations only make alliances within their own industry). I then inverted this measure by dividing 10,000 by the resulting HHI in order to create an increasing measure of diversity. Industries are measured at the two-digit level, and the measure is calculated yearly.

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[14] Notably, since software firms often make use of copyright protection rather than patents, using patents to assess the shock may underestimate the effect of the shock on the software industry, making this a somewhat conservative test.

Percent IT Alliances. I will examine how the technology shock changes the degree to which firms select partners in the IT industries using a yearly measure of the percent of an industry's alliances that are formed with partners in IT industries.

Patents. I measure the variable, $Patents_{it}$, as the number of successful patent applications for firm *i* in year *t*. I used the Delphion database to collect yearly patent counts for each of the firms, aggregating subsidiary patents up to the ultimate parent level. Granted patents were counted in their year of application. Yearly patent counts were created for each firm for the period of 1990 to 2003 (based on application date), enabling different lag specifications between the independent variables and patent output, and the creation of a patent stock variable (discussed in the controls section).[15]

One of the challenges with using patents to measure innovation is that the propensity to patent may vary with industry, firm size, or other factors, resulting in a potential source of bias (Levin et al. 1987). I addressed this potential bias in two ways. First, to control for industry level differences in propensity to patent, I use yearly data on industry-level R&D intensity. Second, to control for unobserved factors that influence firm-level propensity to patent, I include a firm-level patent stock variable as described in the controls section, and firm fixed effects to control for unobserved firm-level heterogeneity.

Independent Variables

Technology shock composite measure. To measure the technological shock, I use a composite measure of the growth rate of the internet and technological change in semiconductors (the input that most directly contributes to the advances in networking equipment used to exploit the internet). The former is measured as the yearly percentage increase in internet hosts. The latter is measured as the yearly change in semiconductor total factor productivity. As noted previously, these measures are highly correlated, consistent with my presumption here that they are closely interdependent, and serve as multiple measures of the technological shock in information technology. I thus standardized each measure and added them together to create a single yearly index of the growth rate of the internet and networking technologies.

[15] 2003 was chosen as the last year from which to collect patent data in order to ensure that most of the patent applications had ample time to be granted. As of 2008, the USPTO indicated that the average time between date of application and granting was 22 months. Examination of the patent data used here indicated an average granting time of just under two and half years, with a standard deviation of just over a year, so by permitting nearly five years between application and granting (the data were collected in October of 2008), the data for 2003 should include over 95% of the patent applications that will be ultimately granted.

Firm-level alliance activity$_{ti}$. To capture the effect that a firm's direct alliances have on its subsequent innovation, I include each firm's number of technology alliances formed for three-year windows leading up to and including the observation year (e.g., thus the observation for 1992 includes alliances formed in 1990 – 1992).[16] This data was collected from SDC, as described earlier in the paper, and log transformed to improve its normality.

Firm-level network reach$_{ti}$. To assess the network effect on innovation, I use a measure that captures both the size of the network component within which a firm is embedded, and the average path length of the firm to each other member in its component (which is affected by both the structure of the component, and the centrality of the firm in question). The more firms that can be reached by any path from a given firm, the more knowledge that firm can potentially access. However, the likelihood, speed, and integrity of knowledge transfer between two firms are directly related to the path length separating those two firms. The diffusion of information and knowledge occurs more rapidly and with more integrity in networks with short average path lengths than in networks with longer paths (Watts 1999). A firm that is connected to a large number of firms by a short average path can reach more information, and can do so quickly and with less risk of information distortion than a firm that is connected to fewer firms or by longer paths. To capture this I use *distance-weighted reach*.

Distance-weighted reach is the sum of the reciprocal distances to every organization that is reachable from a given firm, i.e., $\sum_j 1/ d_{ij}$, where d_{ij} is defined as the minimum distance (geodesic), d, from a focal firm i to partner j, where $i \neq j$. For example, a firm that is directly connected to two other organizations (that are not connected to each other) will have a distance-weighted reach of two. A firm that is directly connected to one other organization that, in turn, is directly connected to one other organization, will have a distance weighted reach of 1.5. Other things being equal, a firm's network reach will increase with the size of the component within which it is embedded, the shortness of path lengths in that network (which decreases with the density of the network or with centralization of the network, as when many organizations are all connected to the same central "hub"), and the firm's centrality within that component.

The preceding reveals one of the key benefits of using distance-weighted reach: it provides a meaningful

[16] Both the firm-level alliance counts and the distance-weighted reach measures are based on three-year windows because alliances often endure longer than one year, thus using only a single year tends to bias downwards alliance counts and measures of network connectivity. Robinson and Stuart (2007) use a similar approach in assessing alliance networks in the biotechnology industry.

measure of the size and connectivity of firms' reachable networks, even when the overall network has multiple components, and/or component structure is changing over time. It avoids the infinite path length problem typically associated with disconnected networks by measuring only the path length between connected pairs of nodes and it provides a more meaningful measure than the simple average path length between connected pairs by factoring in the size of connected components.[17] The distance-weighted reach for each firm was obtained from the network analysis conducted at the beginning of the paper. Thus it is based on the firm's position in the global technology collaboration network and includes any type of other reachable organization. The measure was log transformed to improve its normality.

Controls

Sales$_{ti}$ To control for firm size, I include yearly sales data as obtained from Compustat. The measure is log transformed to improve its normality.

R&D$_{ti}$ To control for firm-level emphasis on innovation, I include a firm's yearly R&D investment, as obtained from Compustat. Notably, I used absolute R&D figures for firms rather than R&D intensity since a firm's total number of patents produced is likely to be much more closely related to its total R&D expenditures than to its R&D expenditures normalized by sales. The measure is log transformed to improve its normality.

Industry R&D Intensity$_{tj}$. To control for differences in the emphasis on and costliness of innovation across industries, I employ a time-varying measure of industry-level R&D intensity (industry-level R&D expenditures/Industry Sales). I collected annual R&D expenditures and sales of firms in each industry (two-digit SIC) from Compustat.

***Patent Stock$_{ti}$*.** To control for unobserved heterogeneity in firm patenting, I follow an approach similar to that used in Blundell, Griffith and Van Reenen (1995) and calculate the variable *Patent Stock$_{ti}$* for each firm as the sum of successful patents applied for in the three years leading up to and including the observation year. This variable is then natural log transformed. Since the dependent variable is always lagged by at least one year, the patents counted for the dependent variable do not overlap with the patent stock variable.

Model Specification for the Patent Studies

[17] I am grateful to Steve Borgatti for pointing this out. I am also grateful to Mark Newman for numerous discussions about how to handle the infinite path length consideration in disconnected networks.

The dependent variable in this study, *Patents* $_{ti}$, is a count variable and takes on only non-negative integer values. The linear regression model is inadequate for modeling such variables since the distribution of residuals will be heteroscedastic non-normal. A Poisson regression approach is appropriate to model count data (Hausman, Hall & Griliches 1984). However, the Poisson distribution contains the strong assumption that the mean and variance are equal. Patent data often exhibit overdispersion, where the variance exceeds the mean (Hausman, Hall & Griliches 1984). In the presence of overdispersion, coefficients will be estimated consistently but their standard errors will generally be underestimated, leading to spuriously high levels of significance (Cameron & Trivedi 1986). Each model reported here exhibited significant overdispersion when estimated using the Poisson specification.

A commonly used alternative to the Poisson regression model is the negative binomial model. The negative binomial model is a generalization of the Poisson model and allows for overdispersion by incorporating an individual, unobserved effect into the conditional mean (Hausman, Hall & Griliches 1984). To control for unobserved heterogeneity (i.e., the possibility that unmeasured differences among observationally equivalent firms affects their patenting), I employ individual firm fixed effects.

A final estimation issue concerns the appropriate lag structure of the independent variables. Griffin's (2002) study of new product development found that it takes an average of 53 months for firms to develop products that are new to the world, suggesting a four-and-a-half year lag. Similarly, Gomes-Casseres, Hagedoorn and Jaffe (2005) find that when firms cite prior alliance partners in their patents, they are most likely to cite partners they were allied with three to five years prior to the granting of the patent. Other research, however, has typically used shorter lags (e.g., Ahuja 2000; Sampson 2004; Schilling & Phelps 2007; Stuart 2000). I thus estimate models with lags ranging from one to five years to explore the influence of lag structure. All models were estimated with STATA 10.0.

RESULTS

The very high correlation between the technology shock and the number of alliances (hypothesis 1) was already exhibited in the inductive section of the paper, so I proceed here to hypothesis 2. Table 2 shows fixed-effects panel regressions for the first set of dependent variables (alliance industry diversity, and percent IT alliances), for each of three samples: the full sample, non IT industries, and IT industries. For each of the dependent variables I first ran a restricted model with industry dummies to control for industry fixed effects, and then ran the full model so that the change in R squared due to addition of the technology shock index could be assessed. The results indicate positive and significant relationships between alliance industry diversity and the technology shock measure for the pooled sample and for the non-IT industries subsample (p<.01 for both the pooled and non-IT samples), supporting hypothesis 2. There is not, however, a significant relationship between alliance industry diversity and the technology shock measure for the IT industry subsample. I will return to this result in a moment. The results for all three samples also show a positive and significant result between the technology shock measure and the percent of alliances formed with organizations in IT industries (p<.01 for the pooled sample and non-IT sample; p<.05 for the IT sample), supporting hypothesis 3. The results indicate that even though the rapid growth in internet and related technologies led non-IT firms to form alliances with IT firms (and thus, reciprocally IT firms were forming alliances with non-IT firms), IT firms were simultaneously forming an even greater number of alliances with other IT firms, dampening the alliance industry diversity effects.

---------------------Insert Table 2 About Here--------------------------------

The IT shock composite variable has an extremely high correlation with the size of the largest component of the collaboration network (.70, p<.001). This should not be surprising given the data already provided in Table 1, and the network graphics in Figure 9, and provides some support for hypothesis 4. To really test this hypothesis, however, it would be preferable to have data on multiple technology shocks that occurred at different points in time, and multiple ranges of network data. This, unfortunately is not the case here, but remains a possibility for future research.

Table 3 shows the results of the negative binomial models run for firm-level patent data. Models were run for lags ranging from one to five years; the first model in each set is the restricted model (control variables only), the second model includes the technology shock index, the third model adds the firm-level alliances, and the fourth model in each set includes the network reach variable and is the full model. The likelihood ratio test statistic is calculated each time one of the independent variables is added to the model. In nearly every case, the statistic is significant, suggesting that the technology shock, firm-level alliances, and firm-level network reach variable each significantly improve the explanatory power of the models. As shown, when only the technology shock variable is entered, it is positive and significant with every lag, supporting hypothesis 5. When the alliances variable is added, it too is positive and significant for lags of three, four, or five years, and the Sobel test statistic indicates that it significantly mediates the technology shock variable, providing support for hypothesis 6. Similarly, the network reach variable has a significant and positive relationship with subsequent firm patenting with every lag structure used, suggesting that the size and structure of the global technology collaboration network (and firms' positions within it) has a significant effect on firm innovation, above and beyond the effect of the underlying technological opportunity. The Sobel test statistic also indicates that the network reach variable significantly mediates the alliances effect, rendering the direct effect of firm-level alliances insignificant for lags of three years or more (Baron and Kenny, 1986). Thus the results indicate support for hypothesis 7. Finally, entering the collaboration variables lowers the incidence rate ratio for the IT shock variable by 7%, 13%, and 16% for lags of three, four, or five years, respectively. This indicates that a substantive portion of the effect that the technology shock had on innovation was due to its effect on collaboration behavior.

--------------------------Insert Table 3 About Here-----------------------------------

DISCUSSION

This paper was motivated by several fundamental questions about technology shocks, collaboration, and innovation: How do major technology shocks affect the collaboration activities of firms? In particular, does a major shock affect the rate of technology alliance activity? Does it affect partner selection? And how do changes in alliance behavior affect the overall collaboration network? Furthermore, how do changes in the overall collaboration network affect innovation? That is, does the collaboration network influence innovation outcomes above and beyond the effect of the technology shock itself?

To explore the first set of questions about how technology shocks influence alliance behavior and the collaboration network, I first conducted an inductive study of collaboration activity during and after the rise of the internet. This revealed that there was a dramatic spike in technology alliance activity that correlated very strongly with measures of information technology growth. Both the inductive study and a subsequent industry-level panel study of alliance formation indicated that firms shifted their partner selection in response to the technology shock: both IT and non IT firms were much more likely to form alliances with IT firms during the spike. Furthermore, the inductive study showed that the change in alliance activity led to the crystallization of a giant connected component – the world became far more connected. After the spike in alliance activity, however, alliance formation declined just as sharply as it had increased, causing the giant component to disintegrate.

I then turned to the second set of questions: How did the shock and subsequent collaboration activities affect innovation outcomes? To address this, I conducted a large sample panel analysis of patenting by US firms. The results indicated that the technological shock, a firm’s alliance activities, and a firm’s network reach (an outcome of the size and density of the connected component within which a firm is embedded, and the firm’s location within that component) have significant and positive relationships with subsequent patenting output, even when controlling for firm size, prior patenting output, and other unobservable firm-specific effects. The results also show that alliances partially mediate the effect of the technology shock, and network reach partially mediates the effect of alliances. This is a particularly interesting result because though we may not have control over the timing or magnitude of major technology shocks, managers do have control over their alliance activity. Furthermore, the quality of collaboration networks is somewhat amenable to strategic and political intervention. For example, the European Union's EUREKA R&D program plays a large role in organizing the collaborative R&D activities among European companies. MITI performs a similar function in Japan. Research consortia also play a powerful role in structuring relationships among consortia members. All of these organizations are in an excellent position to actively influence the structure of their respective collaborative networks. This suggests that these organizations could benefit from employing network analytic tools and analyzing interfirm networks from a global network perspective.

It is also worth noting that although the giant component that emerged subsequently disintegrated, its transience does not imply that it left no enduring effect. In addition to the innovations that it may have spawned by bringing a broader range of information and resources to connected firms, it created pathways between individuals and firms that did not previously exist. Just as gold rushes leave behind roads, railways, and towns that thrive long after the gold frenzy has dissipated, it is probable that many communication paths that existed in the giant network remained long after the giant component disintegrated. First, we do not know how long many of the alliances lasted – some may be long-lived. Second, even in absence of alliances, communication pathways may exist in the form of personal relationships and referral networks. When individuals work together, they form a transactive memory system about who possesses what kinds of knowledge (Wegner, 1987); this transactive memory system does not immediately expire after alliances terminate.

The data used here is limited in some respects. First, though a much broader range of alliance data was used here than is typical of the ex-ante research (I include data on any type of organization, from any industry, and any nation), it is still limited in that it relies on public announcements of collaboration agreements in the SDC database. Like all alliance databases, this database is incomplete. Furthermore, it neglects informal collaboration agreements. Previous research has shown that the temporal and sectoral patterns in the SDC database are highly reliable despite this incompleteness (Schilling, 2009), but it remains that our understanding of the global technology collaboration network could be refined by more exhaustive databases of both formal and informal collaboration agreements. Second, for the innovation analysis I relied on data on North American publicly-held firms and USPTO patents. In future research, it would be interesting to see if there were differential effects in how the shock and collaboration activity affected the patenting outcomes of non-North American firms, and organizations like universities, government labs, etc.

Despite its limitations, the research offers a number of important contributions to the management and economics literatures on technology shocks, and technological change more generally. First, the data indicate that a shock in technological opportunity can have a profound effect on both the rate of alliance formation and types of partners with whom organizations choose to forge alliances. While previous work has mostly emphasized the self-reinforcing nature of alliance networks (Gulati, 1998; Gulati and Gargiulo, 1999; Goerzen, 2007), the data here show how a major technological shock can disrupt these patterns. When firms face new types of problems, they may seek new types of partners. This has direct implications for understanding the evolutions of organizational fields -- a major technological shock can cause the boundaries of organizational fields to shift and blur, exposing firms to new competitive and institutional pressures.

Second, the research here suggests that there are multiple causal paths between a technology shock and subsequent innovation. The shock itself naturally unleashes innovation opportunities, but in responding to the shock, organizations weave a network that has innovation consequences of its own.

Third, the data indicates that patterns in alliance activity may provide an early signal of a technological shock. As shown in Figure 7, the alliance spike was much more proximate to the spike in information technology measures than other potential indicators such as IT firm foundings, IT firm acquisitions, and R&D spend, suggesting that alliances may be one of first ways that that firms respond to a major technology shock. This is consistent with arguments made in the paper about the role of alliances in responding to uncertainty, and the arguments about alliances being perceived as faster, more reversible, and lower cost options than in-house R&D or acquisitions. The data is also suggestive that large spikes in alliance activity could serve as an early indicator of a technological shock in the environment. It is worth noting that while the information technology bubble and crash were readily observable and well documented, the spike and crash in information technology alliances occurred almost *five years earlier*. Even monitoring the number of times the word "internet" appeared in the Wall Street Journal would not have given early notice of the excitement brewing in the IT industries – this indicator appears to follow the market capitalization of IT firms very closely rather than provide advance notice of it. Monitoring semiconductor total factor productivity growth would have given alert, but this data is usually only available with one or two years lag. Monitoring the growth rate of internet hosts would also have given early warning, though this data was only erratically available until several years later and would have required insight into the nature of the underlying phenomenon (i.e., one would have needed to suspect that there was a boom in internet activity specifically). Alliance data, however, can be tracked daily, and can exhibit patterns without the observer first specifying a particular technological focus. It is thus possible that spikes in alliance activity could provide a valuable early warning system for identifying technological volatility whose impacts will ultimately reverberate through other layers of the economic system.

Finally, this paper assembles and tracks the global collaboration network that exists among all types of organizations, from all industries and nations. Previous research has typically focused on firms in particular industries or regions, implicitly assuming that the bulk of network connectivity occurs within, rather than across, such boundaries. Such choices are highly practical – determining the boundaries of a network is a non-trivial issue, and if network data is to be matched to other covariates (such as financial data or patent data), it may be necessary to constrain the set of organizations examined to those for which data is available. However, examining only one industry, nation, or organization type can overlook significant larger networks. In fact, such extra-regional or extra-industry relationships may be more likely to lead to breakthrough innovations (Ahuja and Lampert, 2001; Fleming, 2001; Hargadon, 2003). One of the intriguing outcomes of the research here is that in many years of the analysis, the global collaboration network was, in fact, a global network. The giant cluster that emerges connects a very large portion of organizations that publicly announced alliances, and is highly centralized around a relatively small number of giant IT and electronics firms. There were no discernible boundaries between geographic regions or industries.[18] This is an interesting finding that has some important implications for future research.

[18] There is, however, an interesting separation that roughly corresponds to all organizations based fundamentally on electronic-based technologies versus chemical-medical-based technologies. This analysis is available from the author upon request.

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Figure 1: Penetration of the Internet: Percent of US Population using the Internet, and Number of Internet Hosts

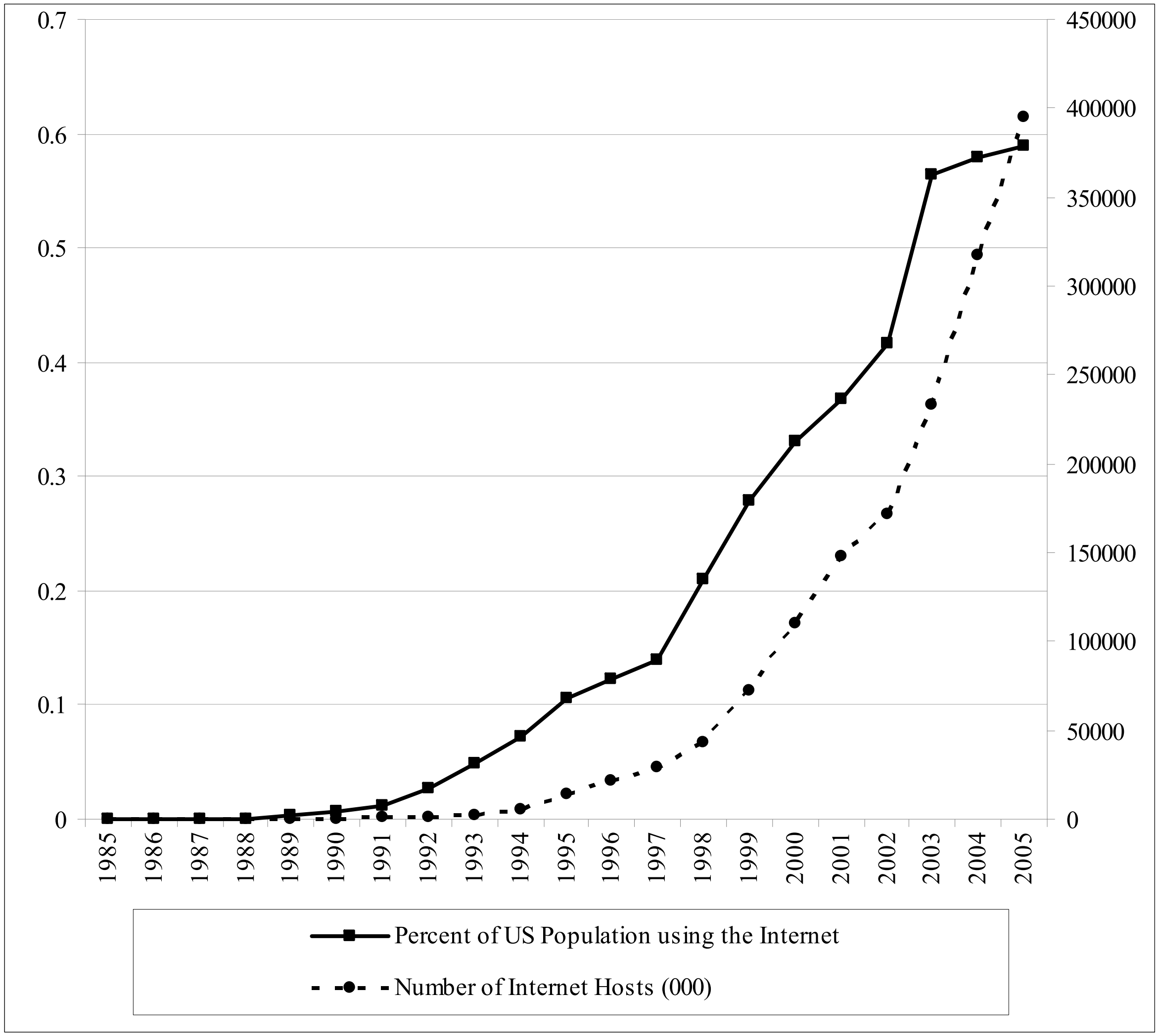

Figure 2: Technology Alliances Reported in Thomson SDC Database

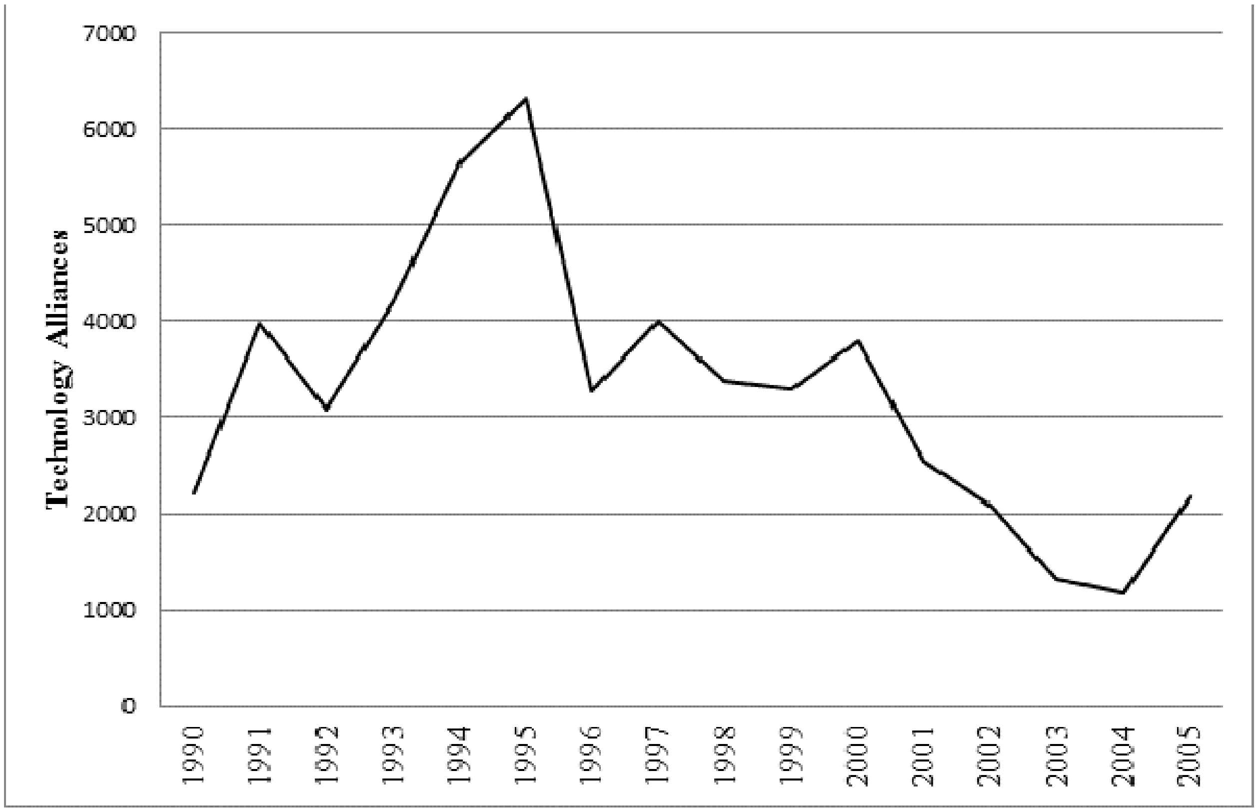

Figure 3: Standardized Number of Alliances Reported in the SDC, CORE, and MERIT-CATI Databases (Biotech Omitted),

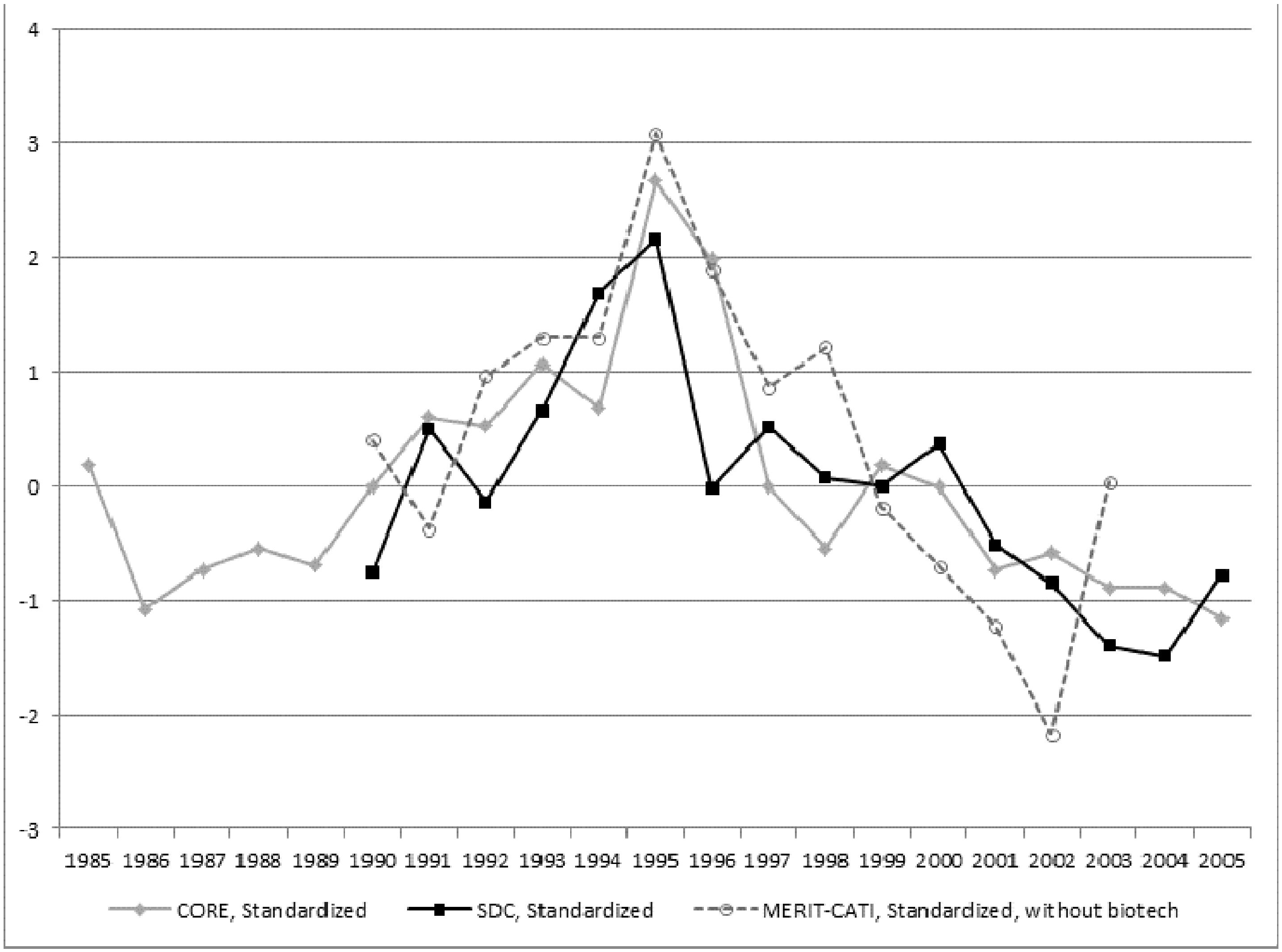

Figure 4: Sectoral Decomposition of SDC Alliances, 1990-2005

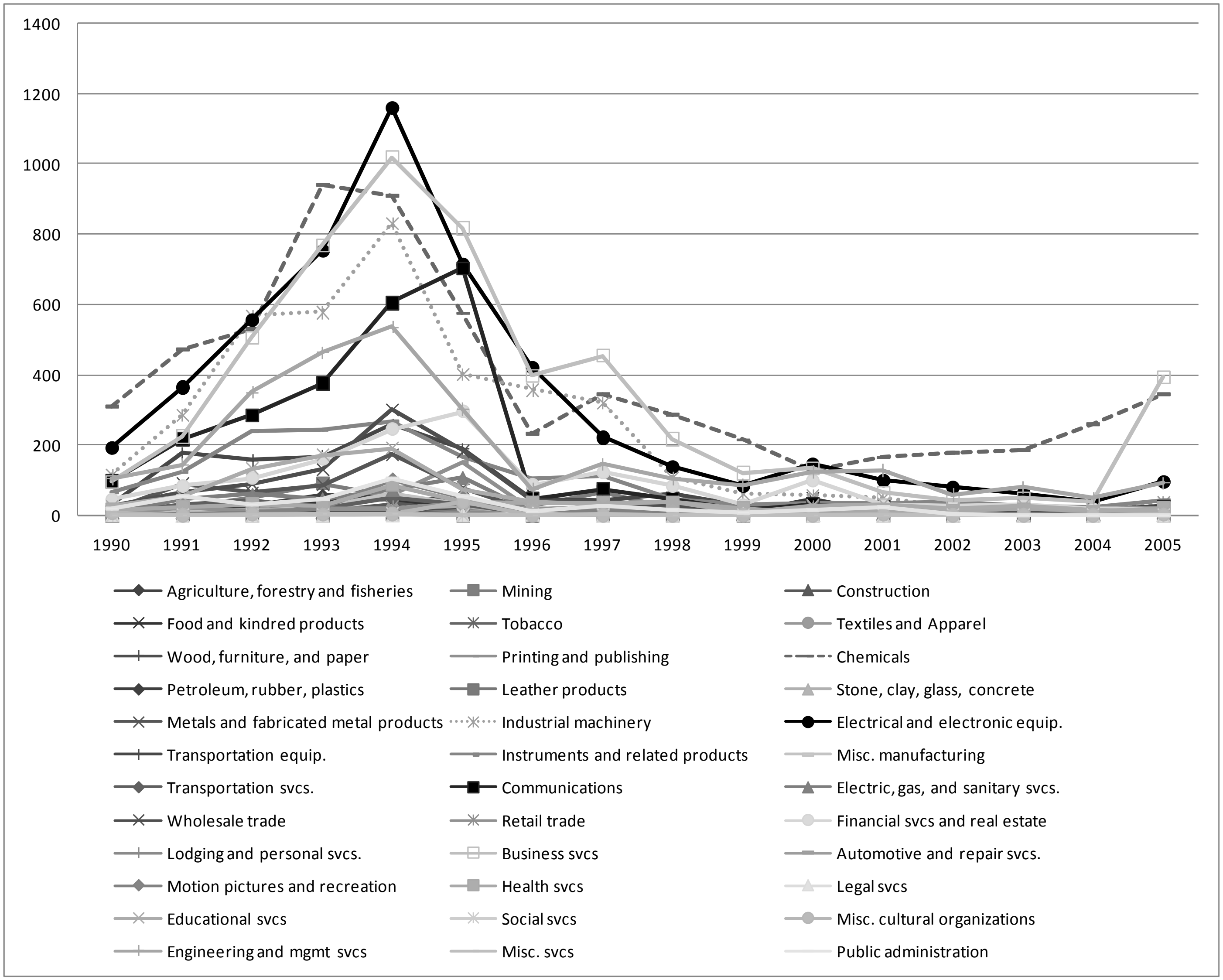

Figure 5: Percent of alliances with dealtext including the terms "cellular phone", "mobile phone", "personal computer", " PC ", "internet" or "network"

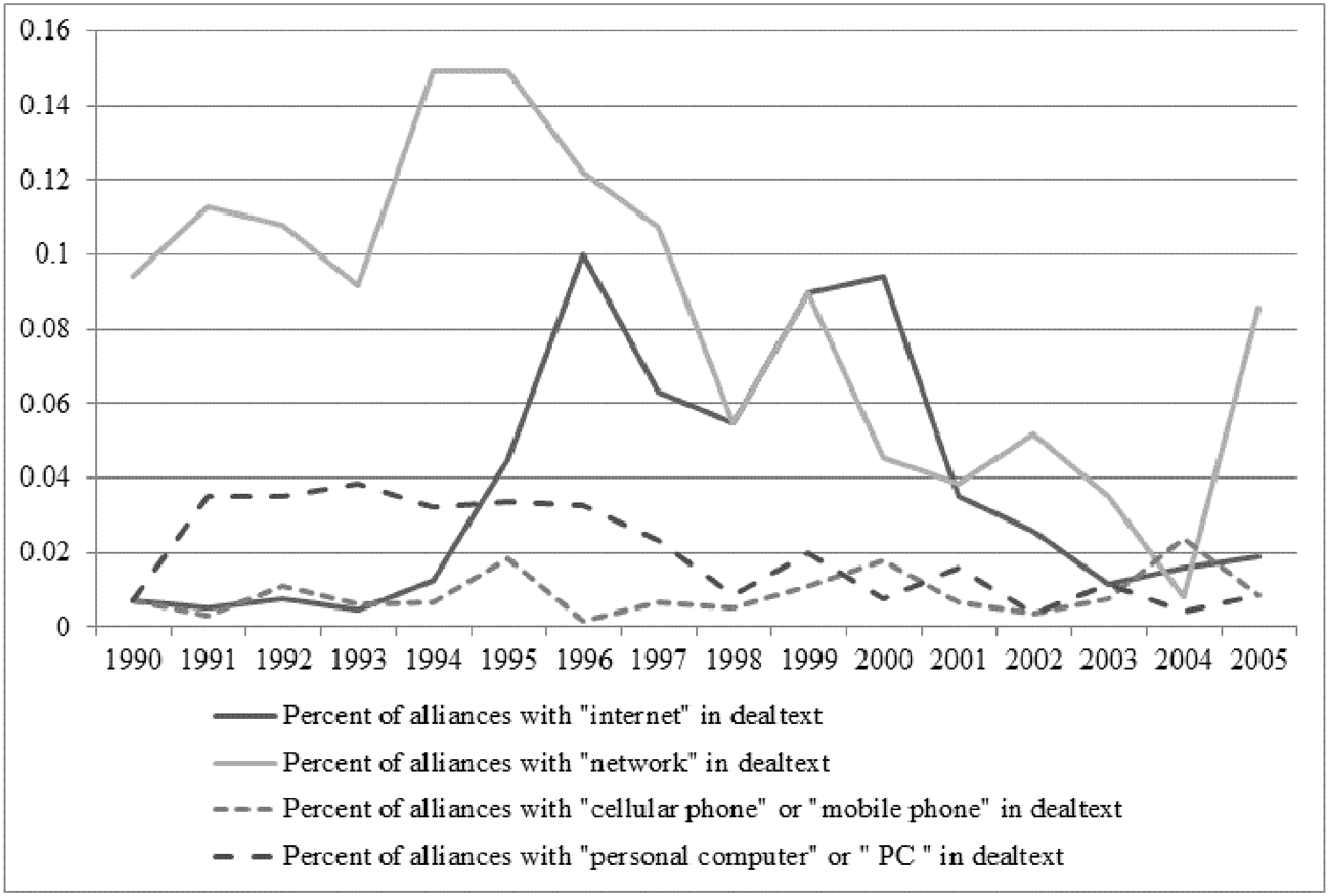

Figure 6: Growth in Internet Hosts and Semiconductor Multifactor Productivity vs. ITAlliances

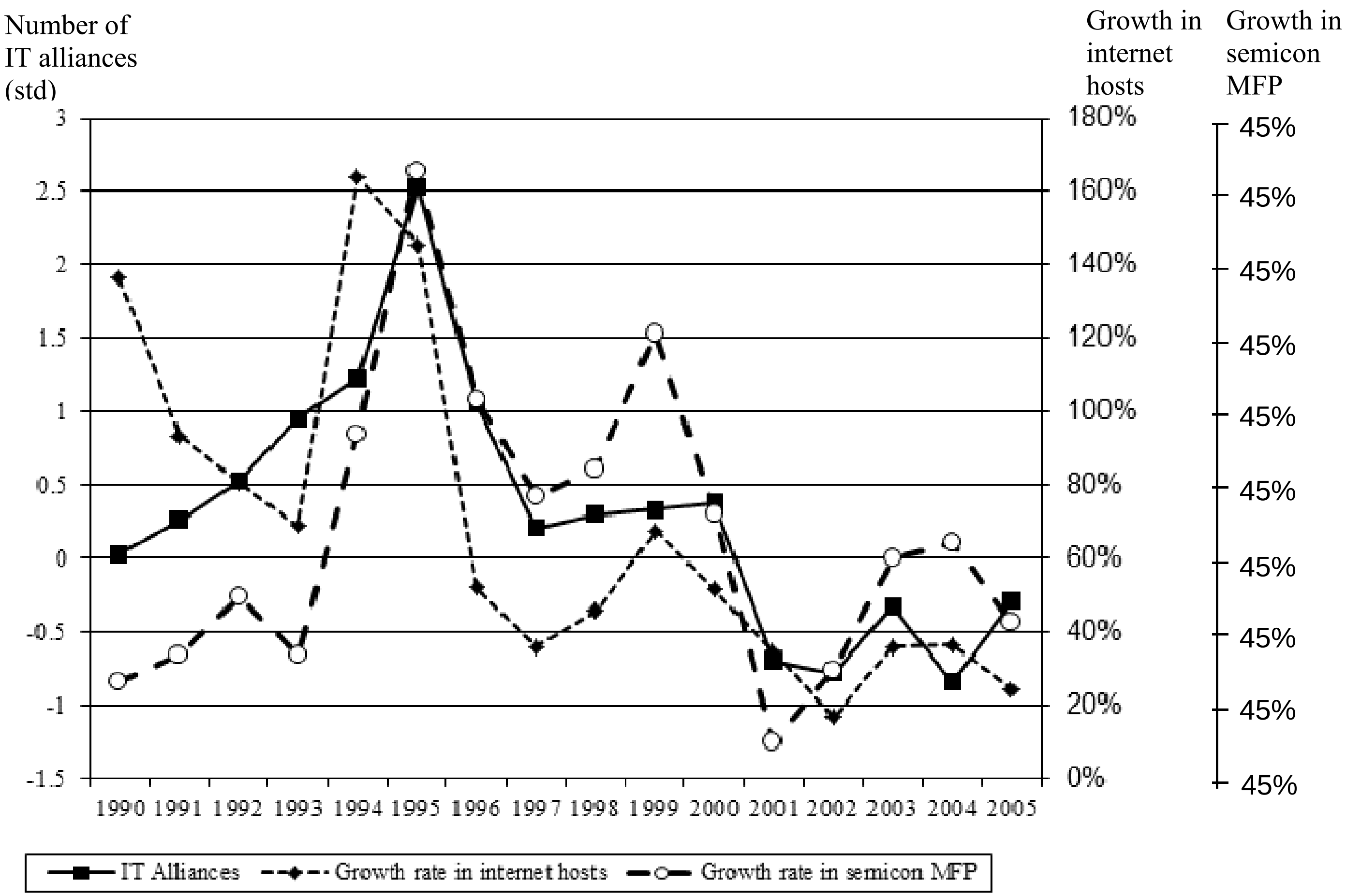

Figure 7: The Internet Technology Shock Rippling Through Layers of the Economic System

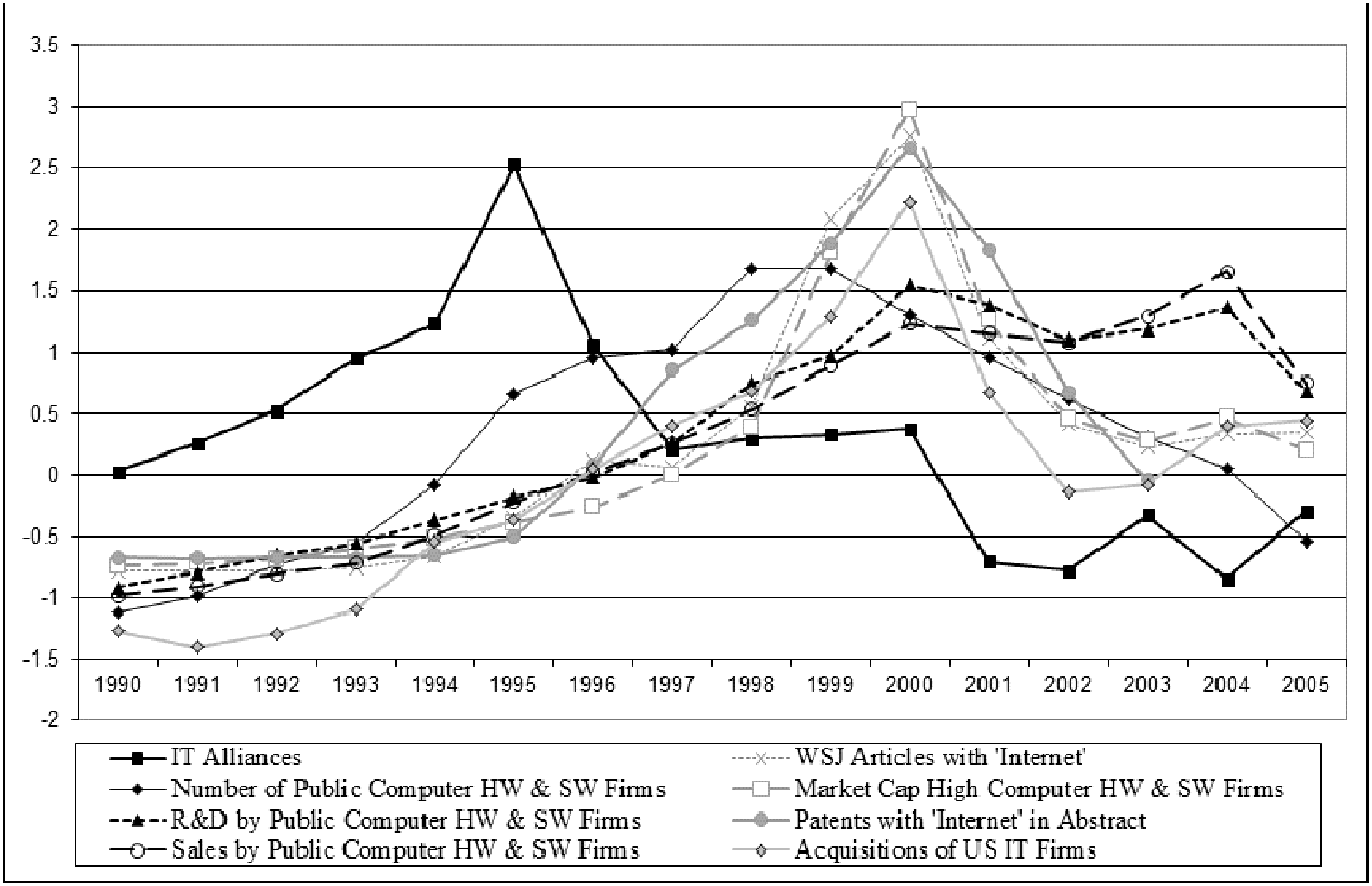

Figure 7: Percent of Alliances formed with firms in IT industries

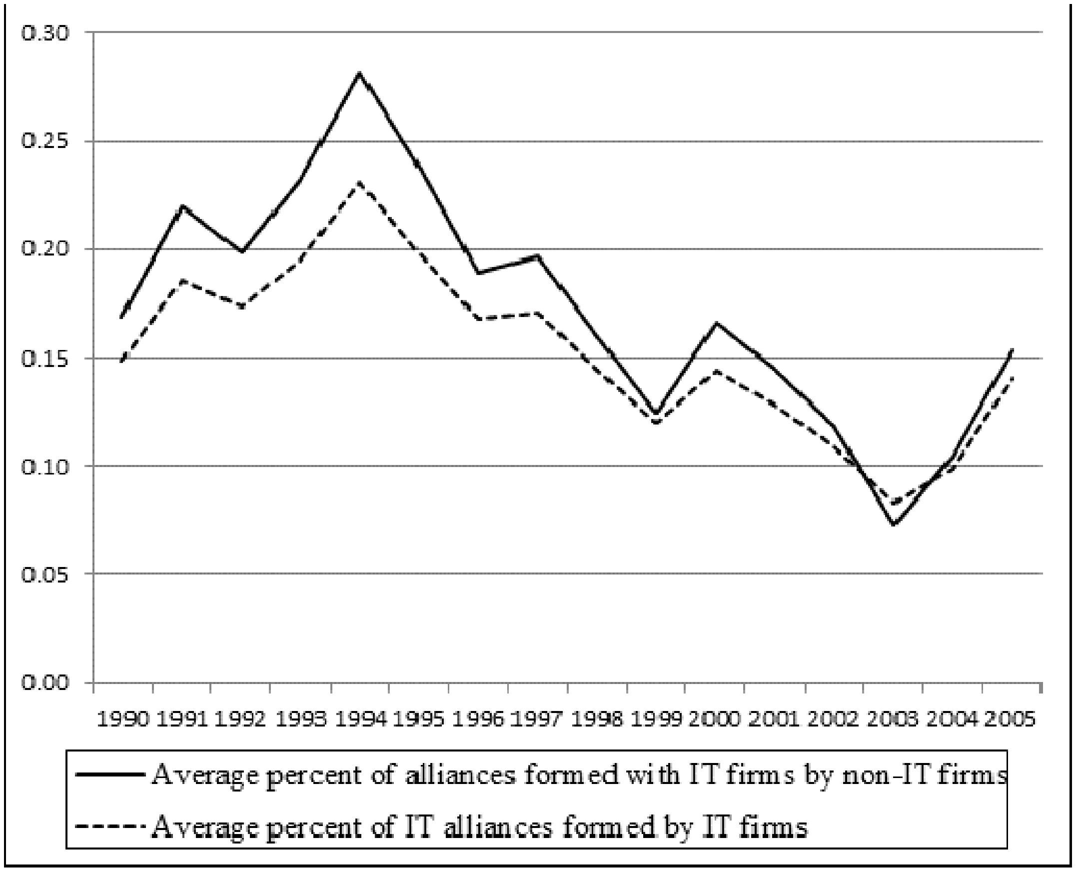

Figure 9: Global Technology Collaboration Network, 1990-2005, one-year snapshots

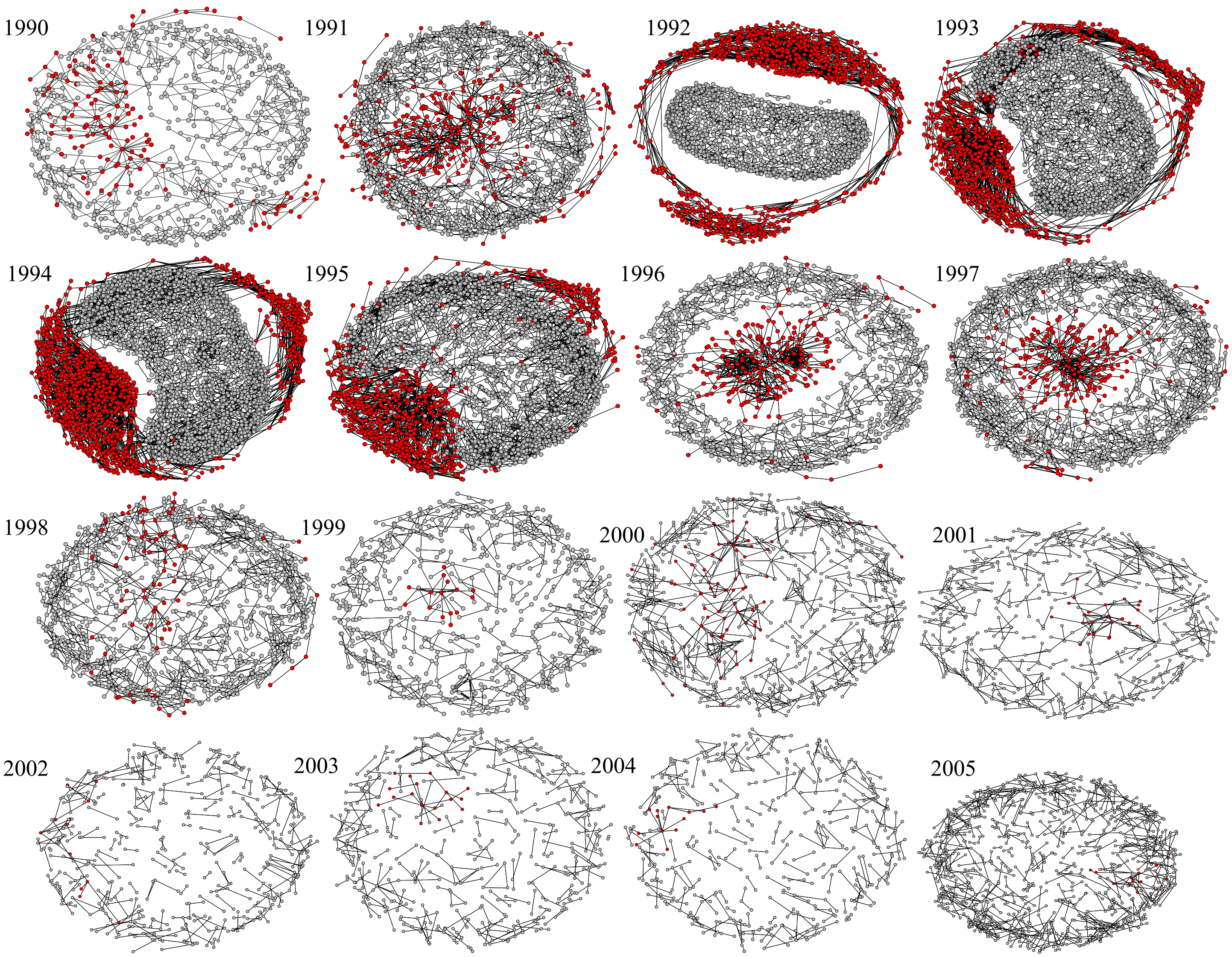

Figure 10: Technology shocks, technological collaboration, and innovation outcomes

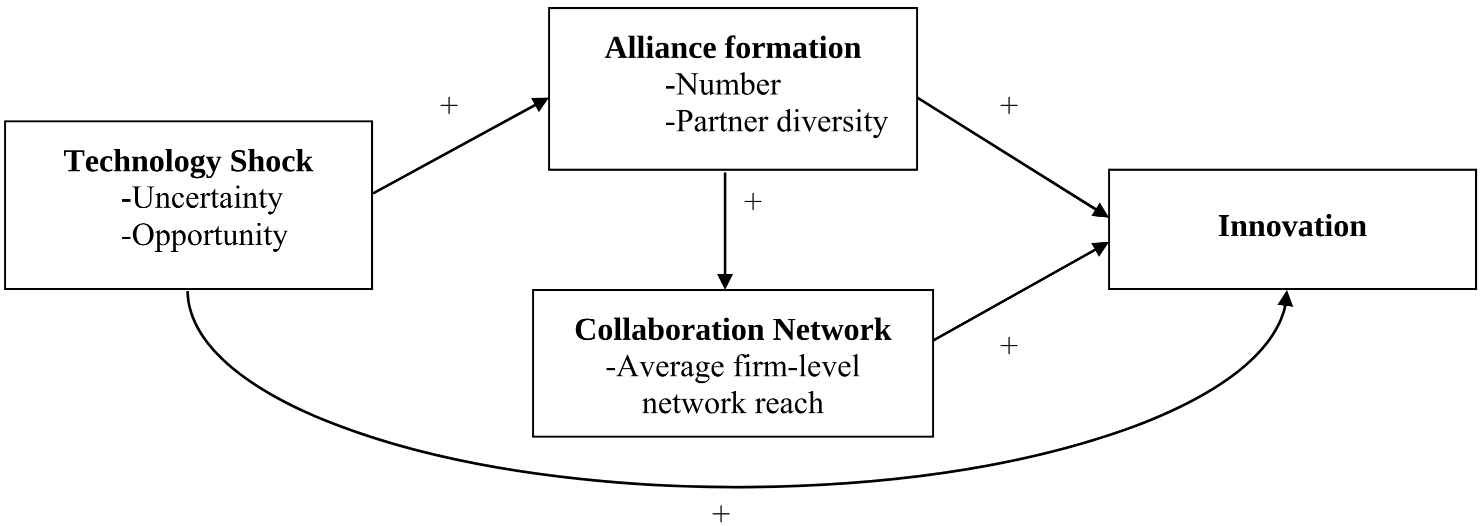

Table 1: Structural Properties of the Global Technology Collaboration Network

Snapshot	Number of participants in network	Average number of agreements per participant (degree)	Largest Connected Component		
			Number of participants	Percent of participants	Degree of participants
1990	683	1.87	128	19%	3.17
1991	1375	1.96	321	23%	3.46
1992	1963	2.16	906	46%	3.18
1993	2505	2.27	962	38%	3.62
1994	3176	2.40	1220	38%	3.91
1995	2865	1.91	799	28%	2.94
1996	1074	2.01	200	19%	5.28
1997	1409	1.68	222	16%	3.24
1998	1023	1.43	79	8%	2.63
1999	629	1.29	16	3%	3.00
2000	722	1.49	73	10%	2.85
2001	567	1.39	23	4%	3.30
2002	489	1.18	12	2%	1.83
2003	476	1.24	17	4%	1.88
2004	452	1.19	13	3%	1.85
2005	1050	1.20	15	1%	1.87
Average	1279	1.67	313	16%	3.00

Table 2: Fixed Effect Panel Regressions

	Alliance Industry Diversity		Percent IT Alliances	
	Rest.	Full	Rest.	Full
<u>All Industries</u>				
Constant	3.63**	3.63**	.00	.00
	(.47)	(.46)	(.06)	(.06)
Industry controls	[a]	[a]	[a]	[a]
Technological change index		.28**		.02**
		(.06)		(.00)
Adj. R squared	.39	.43	.34	.35
F of change		18.89**		18.37**
N	287.00	287.00	1279.00	1279.00
<u>Non IT Industries</u>				
Constant	3.27**	3.27**	.00	.00
	(.51)	(.49)	(.06)	(.06)
Industry controls	[a]	[a]	[a]	[a]
Technological change index		.38**		.02**
		(.08)		(.00)
Adj. R squared	.39	.45	.19	.20
F of change		22.92**		16.91**
N	223.00	223.00	1215.00	1215.00
<u>IT Industries</u>				
Constant	5.83**	5.83**	.69**	.69**
	(.26)	(.26)	(.03)	(.03)
Industry controls	[a]	[a]	[a]	[a]
Technological change index		-.06		.02*
		(.08)		(.01)
Adj. R squared	.38	.37	.06	.10
F of change		.58		4.10*
N	63.00	63.00	63.00	63.00

* p<.05; **p<.01
[a] Coefficients for industries omitted to preserve space

Table 3: Fixed Effects Negative Binomial Panel Model Results

	Patents$_{t+1}$				Patents$_{t+2}$				Patents$_{t+3}$			
Variables	1	2	3	4	1	2	3	4	1	2	3	4
LN(Sales)$_{ti}$	.03	.04	.04	.04*	.03	.04*	.05*	.05*	.03	.04*	.05*	.05*
	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
LN(R&D)$_{ti}$	.02	.01	.01	.00	.02	.00	-.00	-.01	.00	-.01	-.02	-.02
	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)
Industry RDI$_{tj}$	-.36	2.78*	2.96*	3.84**	-2.13	3.93**	4.34**	4.87**	-4.73**	1.12	1.86	2.13
	(1.24)	(1.41)	(1.43)	(1.45)	(1.34)	(1.51)	(1.53)	(1.55)	(1.43)	(1.58)	(1.60)	(1.62)
LN(Patent stock) $_{ti}$	.45**	.46**	.46**	.47**	.33**	.36**	.35**	.36**	.26**	.29**	.29**	.30**
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)	(.02)
Technology shock index $_{t}$		.08**	.08**	.02		.18**	.17**	.13**		.21**	.18**	.13**
		(.02)	(.02)	(.02)		(.02)	(.02)	(.02)		(.02)	(.02)	(.03)
LN(Number of alliances)$_{ti}$			.01	-.00**			.04	-.00*			.08**	-.00
			(.02)	(.00)			(.03)	(.00)			(.03)	(.00)
Network reach $_{ti}$				.03**				.03**				.03**
				(.01)				(.01)				(.01)
Constant	-1.21**	-1.46**	-1.49**	-1.59**	-.92**	-1.47**	-1.52**	-1.57**	-.68	-1.25**	-1.34**	-1.35**
	(.09)	(.11)	(.11)	(.11)	(.10)	(.11)	(.12)	(.12)	(.10)	(.12)	(.12)	(.12)
Observations	2814	2814	2814	2814	2814	2814	2814	2814	2814	2814	2814	2814
Groups	409	409	409	409	409	409	409	409	409	409	409	409
Wald χ^2	1436.72	1454.17	1454.99	1496.40	862.47	1001.39	1013.87	1017.09	523.33	673	702.94	695.88
Log likelihood	-7414	-7400	-7400	-7387	-7682	-7629	-7627	-7624	-7765	-7705	-7700	-7696
Likelihood ratio test statistic		28**	0	26**		106**	4*	6*		120**	10**	8**
Sobel test (alliances)			0				1.3				2.6**	
Sobel test (Network reach)				3.0**				3.0**				3.0**

† p<.10; * p<.05; **p<.01

Table 3: Fixed Effects Negative Binomial Panel Model Results (continued)

	Patents$_{t+4}$				Patents$_{t+5}$			
Variables	1	2	3	4	1	2	3	4
LN(Sales)$_{ti}$	.04	.05*	.05*	.05*	.01	..02	.02	.02
	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
LN(R&D)$_{ti}$	-.04	-.05	-.07*	-.07*	-.02	-.02	-.03	-.03
	(.03)	(.03)	(.03)	(.03)	(.03	(.03)	(.03)	(.03)
Industry RDI$_{tj}$	-3.09*	2.27	3.27	3.92*	-5.50**	-2.48	-1.88	-.81
	(1.57)	(1.71_	(1.72)	(1.75)	(1.69)	(1.80)	(1.81)	(1.84
LN(Patent stock)$_{ti}$	.23**	.25**	.24**	.26**	.19**	.20**	.20**	.21**
	(.02)	(.02)	(.02)	(.02)	(.01)	(.02)	(.02)	(.02)
Technology shock index$_{t}$		.21**	.18**	.10**		.16**	.14**	.04
		(.02)	(.02)	(.03)		(.02)	(.02)	(.03)
LN(Number of alliances)$_{ti}$			.12**	.00			.08*	.00
			(.03)	(.00)			(.03)	(.00)
Network reach$_{ti}$				.04**				.04**
				(.01)				(.01)
Constant	-.57**	-1.11**	-1.24**	-1.24**	-.26*	-.61**	-.69**	-.75**
	(.11)	(.13)	(.13)	(.13)	(.12)	(.14)	(.14)	(.14)
Observations	2744	2744	2744	2744	2629	2629	2629	2629
Groups	409	409	409	409	408	408	408	408
Wald χ^2	304.39	421.4	450.57	464.51	177.35	220.9	229.64	262.60
Log likelihood	-7348	-7298	-7291	-7284	-6790	-6770	-6767	-6754
Likelihood ratio test statistic		100**	14**	14**		40**	6*	26**
Sobel test (alliances)			3.8**				12.48**	
Sobel test (Network reach)				4.0**				3.97**

† p<.10; * p<.05; **p<.01