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Centrality of government and universities to innovation in the United States: A social-networking analysis

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Abstract

This study explores research collaborations in the United States and the position government and universities occupy in that space through the lens of social networks. Joint organizational patents establish the network. Over time, a dense core of interconnected collaborators forms at the network's heart, surrounded by a periphery of isolated innovators or fragments of very limited collaborations. Government and research institutes sit at the center of this core and act as hubs through which connections sprawl out. The core goes through two waves of expansion in late 1980s and 2000s. Federal laboratories are the main force behind both. The second wave also bears the hallmarks of second academic revolution, with a larger share of university–industry link formation and less government involvement. Technology also matters. Government and research organizations have traditionally been central to complex and knowledge-intensive technologies such as biotechnology, pharmaceuticals and chemistry. However, their outreach expands especially during the second wave to cover a more diversified portfolio of technologies.

Keywords: Patents, knowledge diffusion, public policy, social networks
JEL codes: D85, O31, O33, O38

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1 Introduction

Federal government alongside state and local governments are an integral part of research infrastructure in the US. In 2021 alone, the US is estimated to have spent a total of $792 billion on Research and Development (R&D), of which about $66 billion (an 8 per cent share) was government's direct expenditures on R&D. With the addition of grants and subsidies to businesses and higher education, federal and non-federal governments contributed a total of $159 billion, almost a 20 per cent share, to R&D.[1]

Besides intramural research, the US government operates a vast network of Federally Funded R&D Centers (FFRDCs). One important function these centers fulfill is acting as a "three-legged stool", a focal point, to connect commercial industry, academia (or non-profit research institutions) and government with the aim of driving innovation, commercialization and policy in novel ways (Mitre, 2015). Historically, about 14 per cent of total expenditures on R&D in the US and a substantial share of patents and innovations are associated with FFRDCs (Jaffe et al., 1998). According to National Science Foundation, currently 43 FFRDCs are active in the US covering a diverse range of activities from engineering and manufacturing to atmospheric studies.

This collaborative aspect, and not the pecuniary contributions, is the main theme of this study. Innovations are increasingly coming about by way of knowledge sharing across organizations rather than relying on intra-firm resources (Powell, 1990; Lynn et al., 1996; Hagedoorn, 2002; Howells, 2006). The trend is no more evident than in the growing incidences of organizations patenting jointly (Hagedoorn, 2003). The rising complexity of innovations, the rapid rate of knowledge creation, and the dispersion of that knowledge and expertise across firms, universities and government laboratories underpins the need for a more collaborative approach to research (Powell et al., 1996; Smith-Doer & Powell, 2005).

Once collaborations evolve into a network, the impact can go beyond merely sourcing knowledge from immediate contacts and encompasses the whole structure of the social network. The firms embedded in such network have better chances of getting exposed, both through formal and informal channels, to new and complementary ideas that float around the structure (Burt, 2004; Dahl & Pedersen, 2004). There is also the potential for actions of

[1]For information on R&D expenditures see National Science Foundation's scoreboard 2021: https://ncses.nsf.gov/data-collections/national-patterns.

an actor to get amplified and reverberate throughout the network (Bramoullé et al., 2014). As Gulati (1998) puts it:

> "Structural embeddedness or positional perspectives on networks go beyond the immediate ties of firms and emphasize the informational value of the structural position these partners occupy in the network. Information travels not only through proximate ties in networks, but through the structure of the network itself."

In such a universe, the position an organization occupies has implications not only for its own capabilities but also for the vibrancy of the network as a whole. Firms at more central positions are shown to have superior innovation performance and more novelty in their innovations (Powell et al., 1996; Baum et al., 2000; Boschma & Ter Val, 2007; Majeed & Breunig, 2023). Their innovative capabilities and accumulated stock of knowledge also spill over onto their connected ties and diffuse through them to the rest of the network (Burt, 2004). Besides, central organizations act as intermediaries that source, compile and disseminate knowledge from and to other organizations (McEvily & Zheer, 1999; Villani et al., 2017). The effectiveness of the focal organization in fulfilling this role derives from its high absorptive capacity not in one field but in diverse fields of knowledge (Tsai, 2001; Giuliani & Bell, 2005).

Why are government and universities more suited to occupy these central positions? For one thing, their focus on research, and basic research in particular, equips them with enough absorptive capacity to fufill their role as a focal point and a knowledge hub (Cohen & Levinthal, 1990; Rosenberg, 1990).

These organizations can also alleviate the costs and risks of building and maintaining ties. On their own, firms have to incur costs in terms of searching for partner(s), information gathering, legal costs, and on-going governance of the alliance (Hansen, 1999; Rangan, 2000; Reuer & Lahiri, 2014). There are also risks from incomplete contracts and moral hazard that could impede tie formation or lead to post-formation instability in the alliance (Kogut, 1989; Oxley, 1997; Sampson, 2004). Firms might be caught up with a free-riding partner or fall under the influence of an intermediary that plays its ties against each other to gain control (Gulati, 1998).

Involving non-market institutions as intermediaries not only reduces these costs but also assists in knowledge diffusion and coordination of research activities (Lynn et al., 1996; Shohet & Pervezer, 1996; McEvily & Zheer, 1999; Howells, 2006). These institutions also bring authority (both legal and economic) to the community (Lynn et al., 1996). The non-market and non-rival nature of these organizations further makes it easier to surmount the reputation and competition issues that plague inter-firm relations (Dasartha, 2023).

Against this backdrop, it is imperative to examine whether government and universities in the US are active in this space and central to innovation. If so, then, in what ways that centrality has changed and evolved over time? Is it on the rise? Or, is the government stepping back? Historically, policy in the US has prioritized market efficiency over non-market solutions by subsidizing innovation and enforcing antitrust (Aram et al., 1992). On the other hand, an increasing reliance on federally funded research in the US implies that government involvement is more important than ever (Fleming et al., 2019).

To shed light on these issues, I conduct a systematic investigation of innovation collaborations through the lens of social networks. I use data from 1975 to 2019 on utility patents granted to US entities to build a network of innovators. Each assignee organization appears as a node in this network. Nodes can be of three types: government, research, and industry. Research nodes bunch universities and non-profit research centers such as hospitals and FFRDC-affiliated entities. Industry is private companies and research labs associated with them. To that, I also add a fourth type that are foreign entities collaborating with at least one US entity. Joint patents make the links between the nodes.

To track the evolution of this network, I look at it over several time periods. Each time period is a six-year rolling window so as to provide a fuller picture of collaborations an entity has built and led. The application of this rolling window is important, since a collaboration takes time to result in a patent and be observed. In Section 2.3, I add more substance to the choice of this six-year window length.

The most notable feature of the network is the formation of a dense core of interconnected innovators. This core is surrounded by a massive periphery of mostly private firms, innovating in isolation or having very limited collaborations.

The core initially begins as a fragmented set of collaborations between a few large enterprises and universities. From there, it rapidly grows in density and becomes one whole interconnected body. Government and research entities have a sizable presence in the core. Using two indexes of network centrality, I am able to show that government and research nodes also occupy the most central positions in there. Together, these two groups of nodes act as hubs from which connections sprawl out. Industry and foreign nodes have comparatively fewer connections and mostly appear on the perimeter of the core.

Over the observed timeline, this core goes through two waves of expansion. The first wave takes pace around 1984 and ends circa 1994, during which the size of core, in terms of node counts, more than triples. The second wave begins around 2003 and goes until circa 2010. The size of core grows by 30 per cent during this wave.

A deeper dive into the data suggests that the force behind the first wave is most possibly the introduction of Federal Technology Transfer Act of 1986, forcing the FFRDCs to take a more active stance in building collaborations with the industry. In fact, almost all the increase in the centrality of government and research organizations during this phase originates from those agencies that sponsor or administer FFRDCs.

FFRDCs also play an important role in the second wave. However, it is mostly universities and research institutes affiliated with FFRDCs that take charge this time. Government's centrality is barely affected during this wave. As such, the wave has the hallmarks of the second academic revolution (Etzkowitz, 1998; Gulbrandsen & Slipersæter, 2007), with a proliferation of university–industry links and the emergence of *entrepreneurial universities*. Either way, government policy or university involvement has been the driving force in the advent or growth of networks.

I follow the analysis with a few robustness test. Universities, in particular, are a collection of departments, hence act as hypernodes with the possibility of their centrality being overestimated. However, breaking down the network by technology class (the closest one gets to departments with patent data) makes has no impact on the implications. Comparing universities to large firms with multiple divisions, similar to departments, does not change the picture either.

The exercises, however, reveal the technology-specific aspect to the centrality of government and research organizations. These organizations have traditionally been the most central to bio- and pharmaceutical and chemistry technologies. The complexity and intensity of knowledge in these fields and the dispersion of that knowledge across firms, government and universities are considered the main reasons why collaboration is so crucial to innovation in these areas (Powell et al., 1996). Over time, however, the centrality of government and research institutes grows across most technology fields, additionally claiming prominence in technologies such as semiconductors, medical technology, and instruments.

Foremost, this study enhances the literature on the social networking view of innovation and its economic impact (Powell, 1990; Podolny & Page, 1998; Smith-Doer & Powell, 2005). The literature traditionally looks at the formation, evolution and governance of such networks between firms (See Gulati, 1998; Gulati et al., 2000, for a review of this literature). There is also a related literature on the positive influence of cross-firm, cross-industry and cross-team collaborations on firm performance and innovative activity (Burt, 2004; Geletkanycz & Hambrick, 1997; Stuart, 2000). McEvily & Zheer (1999) and Lynn et al. (1996) discuss the role of regional institutes, e.g. government and universities, as side players to these networks. This paper puts government and universities firmly at the center of the network, tasking them with building and maintaining the organizational network.

A series of related works have also taken the social network perspective by looking at specific industries. Biotechnology, pharmaceuticals and semiconductors are the most studied industries (Shan et al., 1994; Browning et al., 1995; Podolny & Stuart, 1995; Powell et al., 1996; Stuart, 2000). While the findings from these studies are precise in one sense, they run the risk of missing the bigger picture. The emergence of bio-informatics, biomedical sensors and instruments, for instance, points to a network spanning far beyond one sector and encompassing actors as far and wide as instruments, semiconductors, and digital (see Shokouhmand et al., 2023, for an example). Bramoullé et al. (2014) theorize that knowledge flows especially get amplified in such combinatorial technologies with knowledge bouncing back and forth between different types of actors involved. By taking an unconstrained view of the network, this study is able to unveil the full scale of collaborations, including the inter-sectoral links.

This paper also contributes to the topic of National Innovation System (NIS). In NIS framework, national institutions and policy are bunched together with innovators and resources as one unit in deciding the path of innovation and growth (Nelson, 1993), with the rules of the game often fixed at the institutional level (Acs et al., 2017). As the findings in this paper show, the involvement of institutions goes beyond merely setting policies and rules and also establishes them as facilitators and coordinators.

Lastly, this work relates to the resource-based view of firms. In this theory, inimitable resources owned by a firm are its source of strategic advantage (Ciszewska-Mlanaric & Wasowska, 2015). Gulati (1999) extends that notion by considering the *social capital* held within a network as a complementary resource. One way to access that capital is by outsourcing (Breunig & Bakhtiari, 2013; Bakhtiari, 2023). A more integrated alternative is cooperation (Miotti & Sachwald, 2003).

The remainder of the paper is organized as follows: The patent data used for the analysis is described in the next section. Section 3 looks at the general topology of the innovation networks and points out the existence of a core. In Section 4, I take a closer look at the core and identify two waves of expansion in collaborations. In Section 5, I test for the centrality of government and research organizations in the network and their evolution. I present a few robustness tests in Section 6. The paper is concluded in Section 7.

2 Data and Methodology

2.1 Analysis data

Patent data currently provide the most comprehensive record of innovations that is publicly available. The complementary information that accompanies a granted patent, such as the assignees, inventors, their location, and the patent's technology codes makes patent data a useful source for classifying and analyzing innovations.

I lead the analysis using the data on granted utility patents by the US Patent Office (USPTO). The data is publicly available from https://patentsview.org. The data used in this study is the 2022 release.

A patent jointly assigned to a set of organizations, in particular, suggests collaboration and knowledge sharing. The data, however, does not have any information about which inventor of a patent is affiliated with which assignee of that patent, if any. The ability to confirm that all assignees are represented by at least one inventor in a patent strengthens the case for research collaboration.

Granting this caveat, one indirect way to infer collaboration is to look at the average number of inventors per assignee for joint patents. In the data, the average number of inventors per assignee for patents with more than one assignee is two. One can take this number as indicating collaboration in the weak sense. Only 7 per cent of joint patents have fewer than one inventor per assignee. These latter patents are potentially cases of technology transfer.

There are a few specific fields from the data that I will be using for this study. The name and country of assignees and their type (whether they are individual or an organization) are the main pieces of information that will assist me in classifying various entities.

Government entities or universities are of special interest. For many patents, there are also individuals listed as assignees. In case there is at least one organization listed, the individuals are understood to be employees. I drop a patent if all assignees are individuals. These patents do not come into the picture when discussing inter-organizational collaborations.

The emphasis is also on collaborative research among American organizations. For that reason, I use the country of assignees and drop patents for which all assignees are foreign. I am still keeping foreign assignees that have a joint patent with at least one US entity.

To study the role of government and research entities and the position they occupy in the innovation universe, I need to classify organizations according to their type. The patent data provides a flag for government entities. However, the flag is less than perfect. I additionally apply a supervised text mining to the assignee names for a more precise identification of government and research organizations.[2] The remaining entities are assumed to belong to the industry. These could be private companies or research labs associated with a company. The set of research institutes includes universities, but also hospital research centers and non-profit research centers in charge of FFRDCs.[3] Any research institute associated with government is classified as government and not research. All foreign applicants are labeled as Foreign, regardless of their association.

I use the main Intellectual Property Classification (IPC) of a patent to identify the tech-

[2] In the supervision phase, I carry out multiple rounds of inspection on random blocks of the data and improve the algorithm until no more improvement could be obtained. The R code is available upon request.

[3] I obtain and integrate into the patent data the list of organizations sponsoring or administering FFRDCS, both current and historical, from NSF FFRDC list.

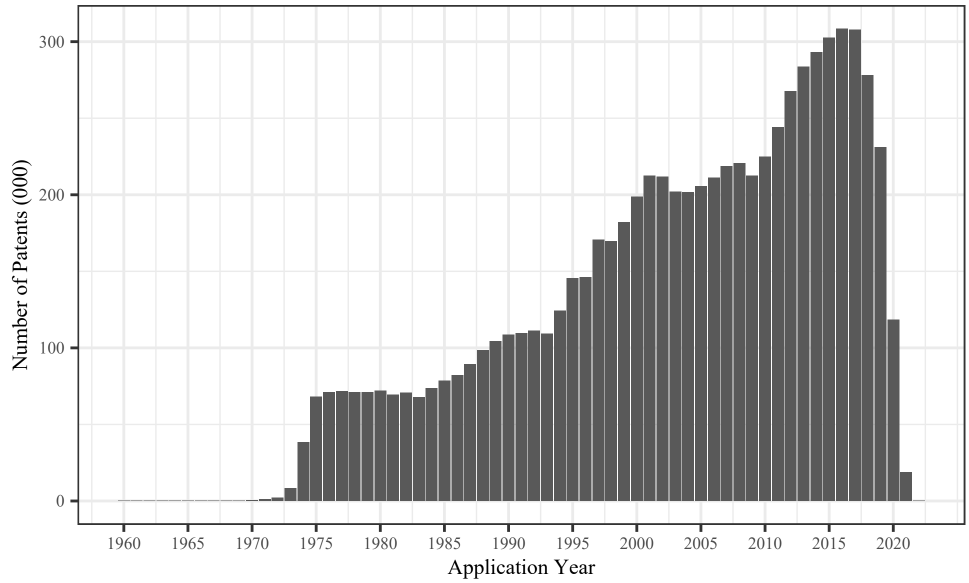


Figure 1: The count of patents by year.

nology it pertains to. Based on the concordance table proposed by Schmoch (2008), these IPCs are mapped onto 11 technology fields for more meaningful presentation.

The timing of a patent is set to its year of application, as it is closer to the time innovation came to fruition. I choose years 1975 to 2019 for inclusion in the analysis. As Figure 1 shows, the number of granted patents in the data jumps up just before 1975. The numbers are also much lower than the trend in 2020 and afterwards, owing to many applications still pending.

2.2 Organizational network

My approach to exploring inter-organization collaborations and centrality of these actors is to picture them as a social network. I treat each distinct assignee as a node in the network. A joint patent between two or more nodes establishes links between them (Figure 2).

I do not allow multiple links, in case the applicants have several joint patents. The links are undirected: knowledge and expertise is assumed to be flowing both ways through the link. As is shown earlier, a small number of patents are about technology transfer, but the direction of transfer is not clear from patent's information.

I additionally label each node by its type as government, research, industry, and foreign to make distinction between the role each group of nodes plays within the network's structure.

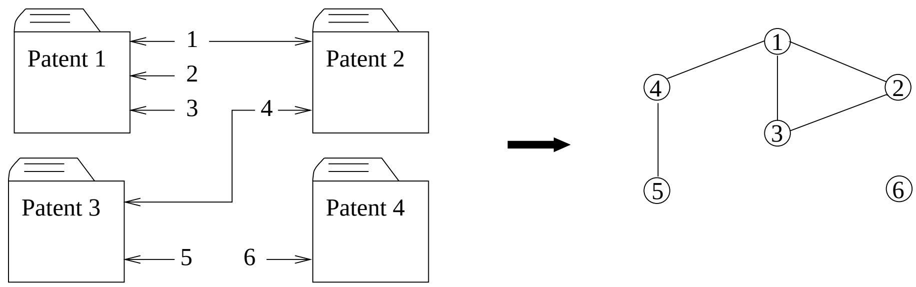


Figure 2: The construction of innovation network from patents. Each applicant is a node in the network. Each joint patent establishes links between the nodes involved.

I will categorize network statistics based on this type assignment.

2.3 Rolling window

In the data, a link tying two organizations is only detected once the patent is granted. A collaboration might have to go on for a few years before resulting in a patent and be observed. Looking at an organization's patenting within only one year is sure to miss many a link and result in a partial observation of the actual network. It is imperative to measure time in units longer than one year to ensure that one captures as full a picture of the network as possible.

There is, however, a trade off when choosing the time-width of the window. Choosing a narrow window will miss a number of links. Choosing a very wide window, on the other hand, smoothes the results to the point that time trends and changes to the network structure become the casualty. Cantner & Graf (2006), for example, use a three-year window to observe R&D cooperations. Having only seven years of data, their choice of this window is probably driven more by data limitations than other considerations.

In this study, I use a rolling window of six years to build the networks. As a rule of thumb, there is a five- to six-year delay from research to innovation on average. As a result, a six-year step is the most compact interval that offers a reasonably complete snapshot of the innovation network.

Figure 3 adds further support to this choice. In this figure, I compute Jaccard's similarity index between two networks, both with the same start year, one formed using window length w and the other using window length $w' = w - 1$. The index has the form (see Batagelj &

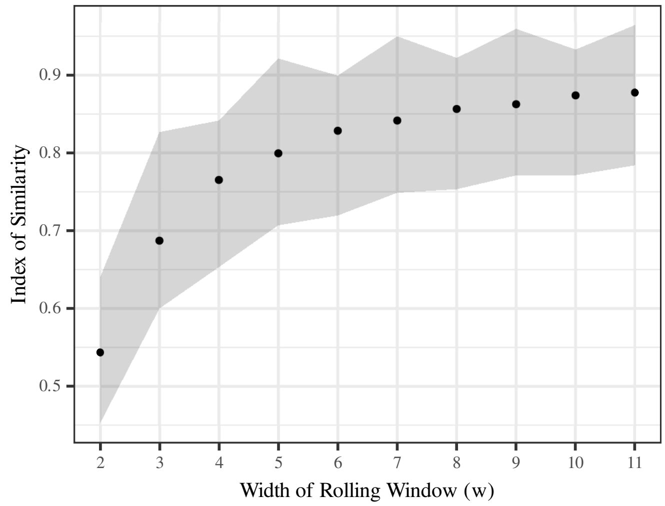


Figure 3: The minimum, maximum and mean Jaccard index for different rolling window widths. Minimum, maximum and means are taken over the range of years for which a network could be constructed.

Bren, 1995)

$$J = \frac{L_{11}}{L_{11} + L_{10} + L_{01}}, \tag{1}$$

in which L is the number of links tying two nodes. L_{11} is the links that are common between the two networks. L_{10} and L_{01} are the number of links that are only in network w' and w, respectively. By construction, $L_{10} = 0$.

The figure is showing the minimum, maximum and average index computed for a pair (w, w'), with these statistics computed over all possible starting years. As the figure shows, there is very little change in the index after a window size of six.

In the remainder, the networks are formed using a six-year rolling window. A different network is formed from scratch for every single period. I form a series of networks for periods starting with years 1975 to 2014 (corresponding to periods 1975–80 and 2014–19) in order to track the time evolution of the innovation network and its structure. The resulting network for period t will have N_t nodes and L_t links.

3 Network Structure

I open the discussion by showcasing a few general statistics describing the networks. These statistics are listed in Table 1 and summarize the size and connectivity of the networks in a few numbers. The table also shows additional statistics on the level of participation by government, research and foreign entities.

The statistics show a substantial expansion in the size of network. The number of nodes almost triples during the observed time-line. Gains in the number of links is even more dramatic. In the last period there are about 20 times more links in the network than they used to in the first period.

Despite the massive growth in size and connectivity, the rate of expansion has not been constant. There is an initial period of rapid expansion. The number of nodes grows at an average annual rate of 4.4 per cent from 1975–80 to 1995–00 (the mid-point). The number of links grows at an average annual rate of 16.2 per cent over the same interval. From 1995–00 to 2014–19, however, the average annual growth in nodes drops to 1.7 per cent. For links the growth rate is only 2.3 per cent.

An increase in the number of links, *per se*, is not indicative of burgeoning collaborations, especially when the number of nodes is increasing in tandem. In the last column of Table 1, I am reporting the normalized number of links or *network density* to account for this fact. Density of a network is defined as

$$Density_t = \frac{2L_t}{N_t(N_t - 1)}. \tag{2}$$

A fully connected network, where each node is connected to every other node, will have $\frac{1}{2}N(N-1)$ links. Index (2) scales the connectivity of a network relative to full connection. The first impression from the densities reported in Table 1 is that the level of collaboration in the innovation network is very sparse.

Despite that, the network's density initially grows fast on par with its size. During the first half interval, the density is growing at an average annual rate of 6.6 per cent. This is the time of flourishing collaborations. That ardor mostly subsides afterwards, with network's density showing very little change over the second half period.

Period	Number of Nodes (N) Total	Govern.	Research	Isolated	Foreign	Number of Links (L)	Density ($\times 10^{-6}$)
1975–80	20,633	26	334	20,241	1	247	1.16
1976–81	20,774	26	356	20,387	1	237	1.10
1977–82	20,875	27	361	20,478	1	250	1.15
1978–83	21,153	26	375	20,738	0	262	1.17
1979–84	21,470	26	393	21,029	0	279	1.21
1980–85	22,077	26	415	21,580	2	324	1.33
1981–86	22,984	28	422	22,448	2	368	1.39
1982–87	24,373	28	453	23,758	3	435	1.46
1983–88	25,944	28	470	25,211	3	534	1.59
1984–89	27,467	31	488	26,622	2	647	1.72
1985–90	29,031	38	496	28,056	3	786	1.87
1986–91	30,464	38	522	29,396	1	901	1.94
1987–92	31,842	38	546	30,651	3	1,054	2.08
1988–93	32,865	36	569	31,520	7	1,282	2.37
1989–94	34,126	35	623	32,585	7	1,615	2.77
1990–95	35,612	34	644	33,809	8	2,028	3.20
1991–96	37,029	27	665	35,061	8	2,264	3.30
1992–97	39,027	29	679	36,833	11	2,640	3.47
1993–98	40,808	28	717	38,436	10	2,904	3.49
1994–99	43,150	30	726	40,586	7	3,191	3.43
1995–00	45,410	29	753	42,700	16	3,360	3.26
1996–01	46,879	30	769	44,098	19	3,381	3.08
1997–02	48,257	32	786	45,387	21	3,520	3.02
1998–03	48,677	33	780	45,809	21	3,494	2.95
1999–04	48,934	35	761	46,085	24	3,503	2.93
2000–05	48,565	36	751	45,805	24	3,448	2.92
2001–06	47,676	33	727	44,987	20	3,400	2.99
2002–07	47,039	32	738	44,433	12	3,455	3.12
2003–08	46,412	35	744	43,817	10	3,544	3.29
2004–09	46,055	35	760	43,478	10	3,630	3.42
2005–10	46,335	33	745	43,755	8	3,713	3.46
2006–11	47,083	35	760	44,437	9	3,884	3.50
2007–12	48,347	37	771	45,646	12	4,033	3.45
2008–13	50,067	37	759	47,283	10	4,195	3.35
2009–14	52,270	38	755	49,352	8	4,488	3.29
2010–15	54,565	41	750	51,518	11	4,718	3.17
2011–16	56,513	41	754	53,386	16	4,935	3.09
2012–17	57,829	43	748	54,699	17	5,013	3.00
2013–18	58,353	43	734	55,277	20	4,993	2.93
2014–19	57,511	45	719	54,604	16	4,695	2.84

Table 1: Simple statistics on the topology of the innovation network in different time periods.

Government and research institutes are the main focus of this study, and I report their numbers separately in Table 1. On average, only about 1.7 per cent of nodes in the networks are associated with government or a research organization. There is also a larger presence of research than government; there are almost 10 times more research nodes than there are government nodes.

Low numbers, however, do not automatically relay insignificance or ineffectiveness in a network. Quite the contrary, it is the position a node occupies relative to structure of the network that dictates its significance and influence (Gulati, 1999; Smith-Doer & Powell, 2005). For instance, a node at the center of a network, connecting to 10 other nodes that, in turn, each connecting to 10 other nodes can have a more seminal role in spawning ideas and innovation given its accumulated human capital and its role as a cross-road for knowledge exchange than a hundred nodes acting in isolation.

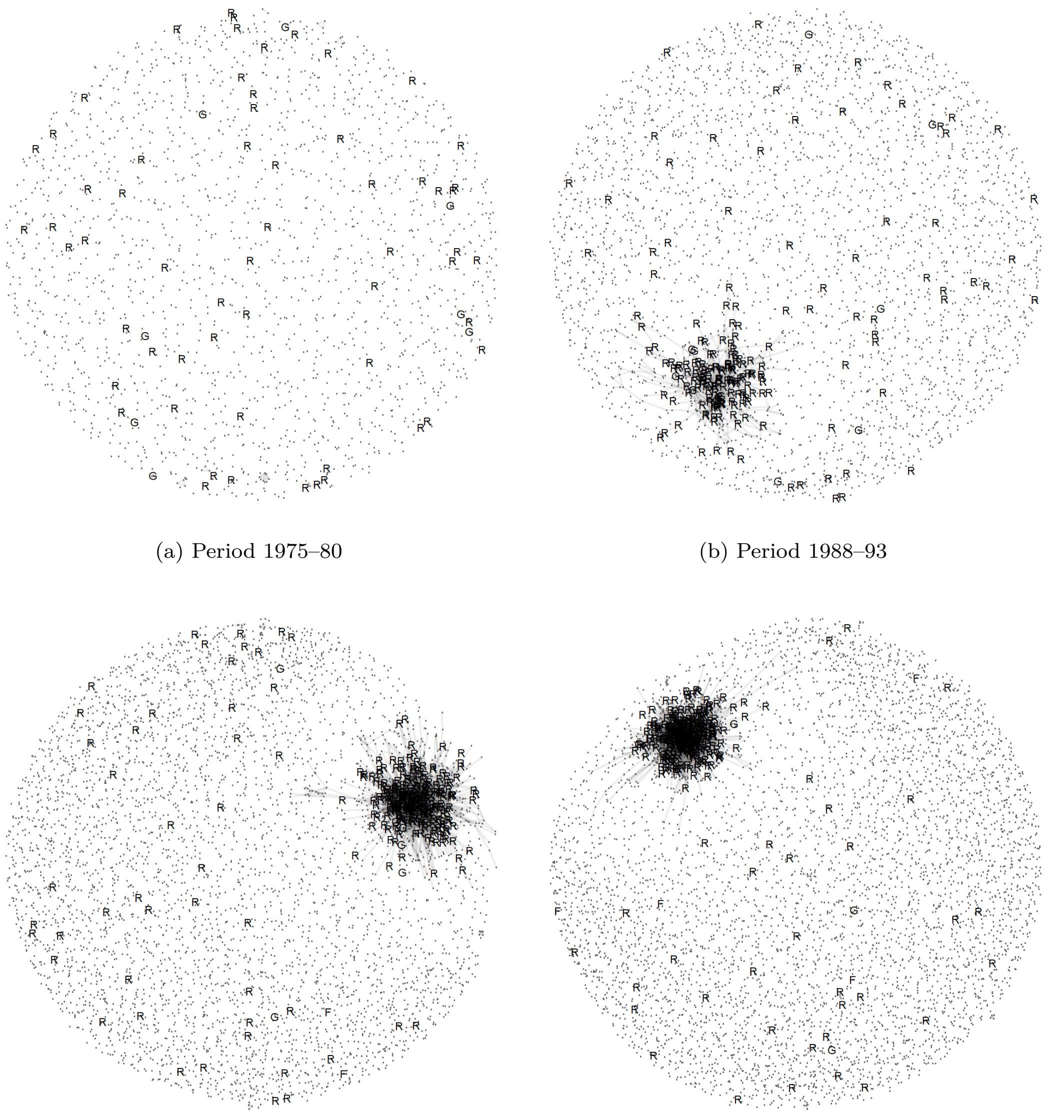
Having said that, the majority of nodes are isolated (Table 1). These are the nodes that have no observed connections to any other node and carry out innovation in total isolation. On average, about 95 per cent of nodes across the innovation network are isolated.

Foreign nodes that collaborate with a US entity are also part of this picture and reported in a separate column of Table 1. There are very few of them. Arguably, US innovation system is fairly insulated from foreign knowledge and mostly relies on its own capabilities.

As a final note, the number of government and research nodes also grows over time, however, at a more moderate yet steadier rate than the overall rate at which the network itself is growing. The rapid expansion of collaborations in the early years, if proved to be driven by government and universities, is not much about more participation by government and research organizations but by them getting proactive in forging ties.

A visual inspection of these networks reveals a few more details about their structure that could not be inferred from Table 1. In Figure 4, I demonstrate four snapshots of the network, equally distanced in time. Given the massive size of the networks, showing the full network obscures the fine details I would like to point out. Consequently, I am showing all connected nodes and only 10 per cent of isolated nodes. One needs only to imagine a much larger cloud of isolated nodes surrounding the patterns to grasp the full scale of each network.

A striking feature of the network is the formation of a core of densely interconnected nodes



(a) Period 1975–80

(b) Period 1988–93

(c) Period 2001–06

(d) Period 2014–19

Figure 4: The graph presentation of innovation networks and the positioning of Government (G), Research (R) and Foreign (F) nodes. To make network details visible, only 10 per cent of nodes with no links are included.

at its center, surrounded by a periphery of colossal proportions (most of which is not shown). In the initial period, there are fragments of collaboration going on. Together, however, they lack the dense structure observed in later periods, hence, might or might not qualify as the core. In the periods that follow, the core expands and collaborations co-join, rendering the core akin to a black hole in the universe of innovators.

Not all collaborations happen in the core. The networks still exhibit a few small pockets of collaboration scattered around the periphery. The periphery is, in essence, a large nebula of isolated nodes or small bits and pieces of linked nodes disconnected from the core.

Government and research nodes are distinguished in these networks, labeled as G and R, respectively. They appear both in the core and around the periphery. However, over time they build a larger presence in the core. In the next Sections, I will add more basis to this observation by having a closer look at the core.

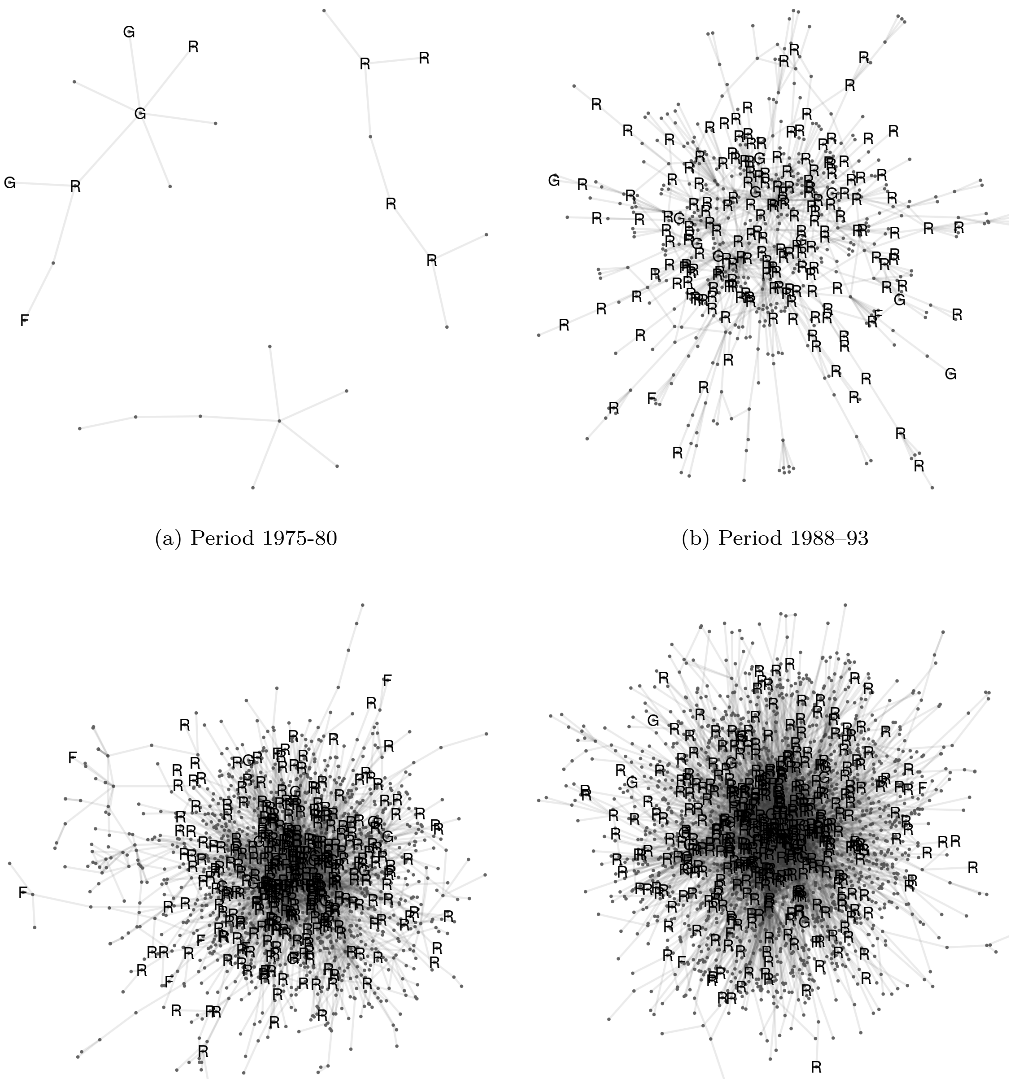
Foreign nodes that collaborate with at least one US entity are also featured in Figure4, labeled as F. Their number pales in comparison to the sheer number of domestic nodes, making them an unobtrusive element of the network. These nodes still play a role through their connections to domestic innovators, but not a central one.

4 The Core

Given its dense structure, the network's core holds the key to centrality. In Figure 5, I am showing the core structure only, for a better look at its structure.

In this figure, one can trace the same changes observed in Figure 4 but with more details. The picture is especially detailed about the formation of the core as it begins with a few fragments and develops into a dense body. Its star-like structure immediately suggests centrality for nodes that are positioned towards the interior.

A sizable chunk of these nodes have either research or government associations. For comparison, in Table 1, the share of government and research nodes from the network was a meager 1.7 per cent. However, within the core, at least one in five nodes is either government or research (Figure 6). Research nodes, e.g. universities, make the bulk of that presence. There is also a visible presence by foreign nodes in the core, which suggests that these nodes are generally connected to the more central nodes.



(a) Period 1975-80

(b) Period 1988–93

(c) Period 2001–06

(d) Period 2014–19

Figure 5: The core structure of innovation network and the positioning of Government (G), Research (R), and Foreign (F) nodes. Lines indicate links between nodes.

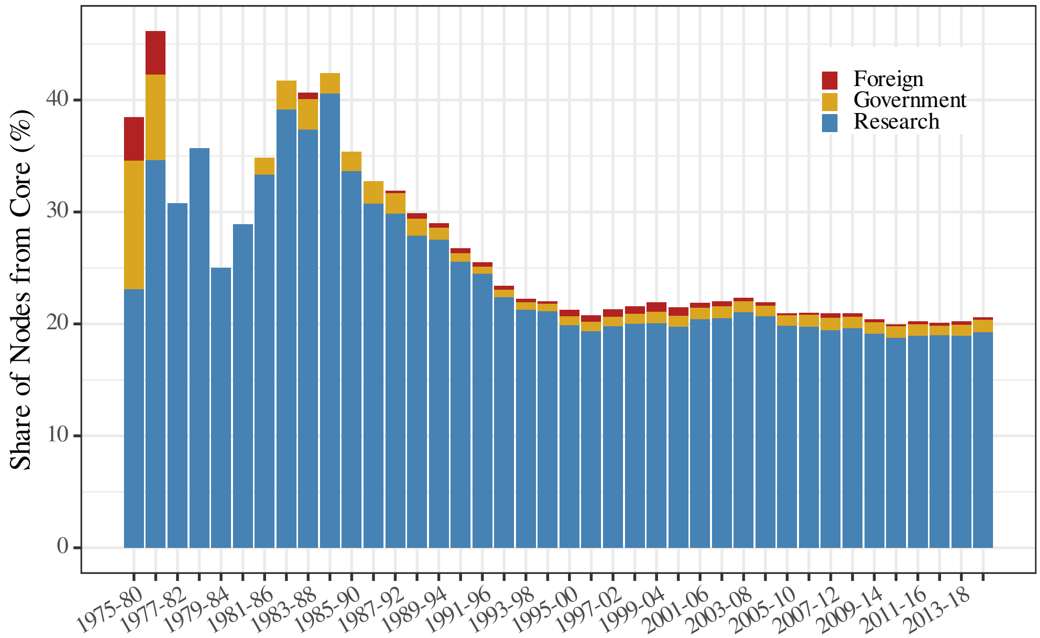


Figure 6: Proportion of government, research, and foreign nodes from the core.

Figure 7 provides a more continuous picture of the core's evolution. The figure illustrates the size of the largest and second largest components of the network over time, where size is defined as the number of nodes. A component, in this context, is a subset of nodes in the network where every pair of nodes is connected through at least one path.

The size of the two components are not very different during the early years. Soon enough, however, a gaping chasm opens between them and the largest component, that is the core, takes over. It follows as a corollary that every pair of nodes in the core has to be connected through at least one path to give the core such a massive structure.

The core being one component has important implications, given information has the chance to travel through the whole connected structure (Gulati, 1998). The larger this structure, the larger the information or social capital it holds and offers to those nodes (Gulati, 1999). Such networks would exhibit higher learning and innovation rates (Dasartha, 2023).

The expansion of the core is not a steady process. There are two major phases. First, there is a rapid and sustained growth that picks up pace around 1984–89 and results in the formation of the core. This episode goes on till about 1994–99. During this stage, the size of core more than triples. By the end of this stage, there are about 1,700 nodes in the core.

A shorter spell of expansion, roughly stretching from 2003–08 to 2010–15, follows. The growth rate during this latter episode is slower. In the end, the size of core reaches 2,200 nodes, a 30 per cent increase over the episode. For easy reference, I will call these two stages waves 1 and 2.

The same dynamics can also be observed in Figure 8. This figure shows the change in the number of nodes in the core by node type, where changes are from period $t-1$ to t. The two waves are more distinctive in this picture. Most of the increase in size is owing to the mass entry of industrial nodes.

There is also a sizable but smaller growth in the number of research nodes in run up to the first wave. In 1980, universities were granted the right to collect loyalties for their patents receiving federal funding. One might be tempted to associate the entry of research nodes into core with this change. However, the trend begins a bit later and is sustained throughout wave 1. The change to patent policy in 1980 cannot explain this feature.

There is also a large drop in the number of core's industry nodes during the last period. This drop is possibly spurious and caused by a number of patents still pending in 2018 and 2019 (Figure 1). A future release of data with more complete list of granted patents would provide a more reliable picture.

5 Centrality

The earlier observations bring up the expectation that government and research nodes should play a central role within the core and to the network as a whole. I will investigate this hypothesis using two indexes of centrality.

5.1 Degree centrality

Government and research organizations do not merely exist in the core, but they have established the largest number of ties, or have the highest *degree* or *popularity* in the parlance of network theory.[4] Degree or popularity of a node is simply the number of its direct links

[4] See Newman (2003) for a dictionary of network terminology and methods.

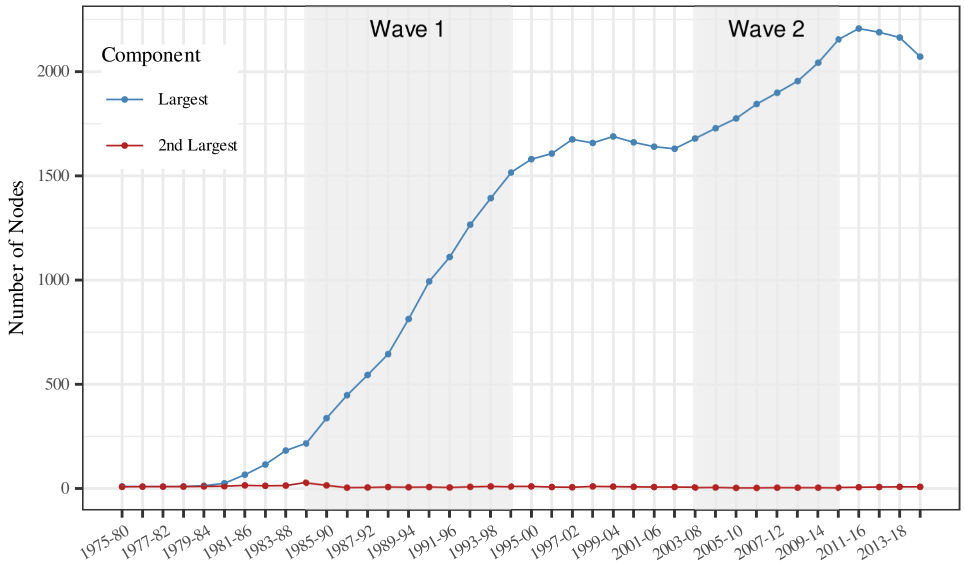


Figure 7: The size of the largest and second largest components in the innovation network over time.

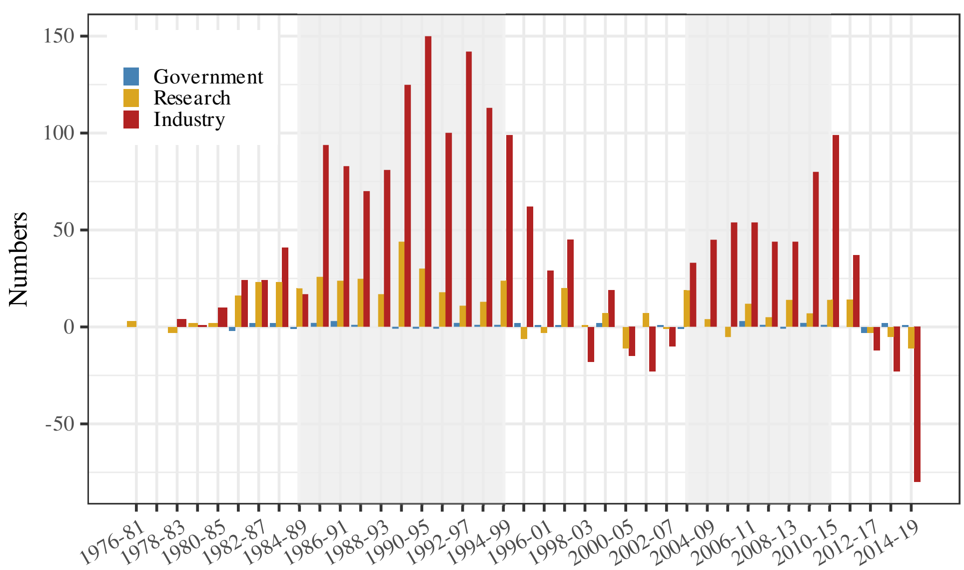


Figure 8: Change in number of nodes in the core by period and type of node.

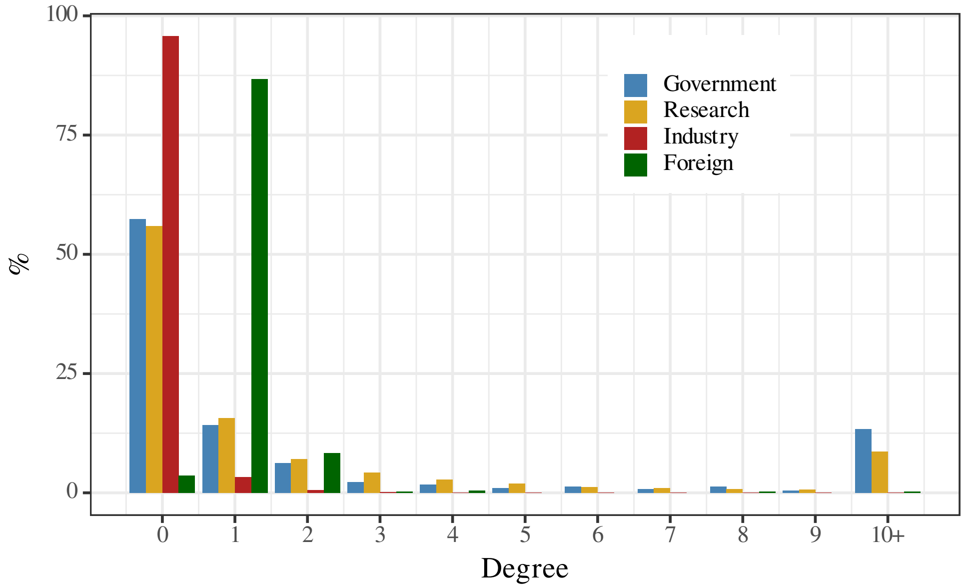


Figure 9: The degree distribution for government, research and industry nodes. Degree of a node is the number of links attached to it. The statistic pools networks from all periods.

and serves as a measure of a node's centrality. In Figure 9, I am showing the distribution of degree by each type of government, research, industry and foreign node.

The distributions all have thin upper-tails. In all cases, except for foreign entities, the largest concentration of nodes is at degree zero, that is, most nodes are isolated. Foreign nodes, by the rule of inclusion, have at least one link, hence, they have their largest concentration at degree one.

For government and research nodes, the proportion of isolated nodes is below 60 per cent, meaning that 40 per cent of these nodes have one or more links. A few of these nodes connect to more than 10 other nodes, giving them a stellar position. In contrast, more than 90 per cent of of industry nodes are isolated. Those collaborating do not have many connections either.

In Figure 10, I investigate how the centrality, or lack thereof, for each type of node tracks over time. In this picture, I am computing the average degree for each type of node. The network's core acts very much as an independent body, detached from rest of the network. Studying central nodes has to focus on the core. For that reason, I look at the core sub-network as a standalone body in panel (a) of the figure and compute the level of centrality

Comparison			Network			Core		
			N_1	N_2	W	N_1	N_2	W
Foreign	>	Industry	56,734	16	79,115.5 [0.000]***	1,648	4	4,246.0 [0.209]
Research	>	Industry	56,734	719	9.05×10^6 [0.000]***	1,648	399	1.51×10^5 [0.000]***
Research	>	Foreign	719	16	391.5 [0.585]	399	4	214.0 [0.011]**
Government	>	Research	45	719	14,949.5 [0.373]	23	399	4,210.0 [0.500]

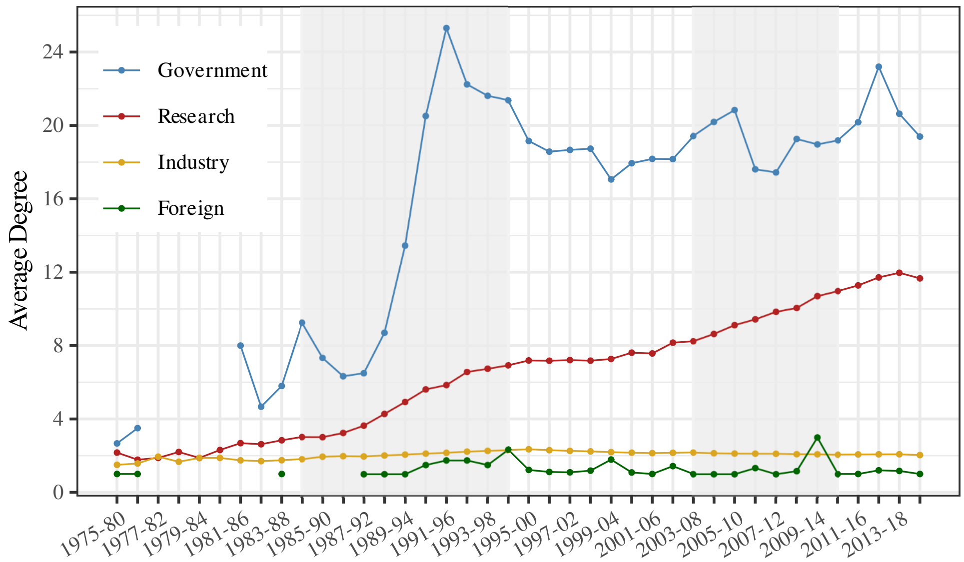
Table 2: Mann–Whitney Rank test of difference in mean degree centrality of different pairs of nodes for 2014–19. Numbers in brackets are p-values. *** and ** denote significance at 1% and 5% levels.

present in there. In panel (b) of same figure, I take average over the full network, considering that not all government and research nodes are a core member and some are forming smaller-scale collaborations in the periphery.

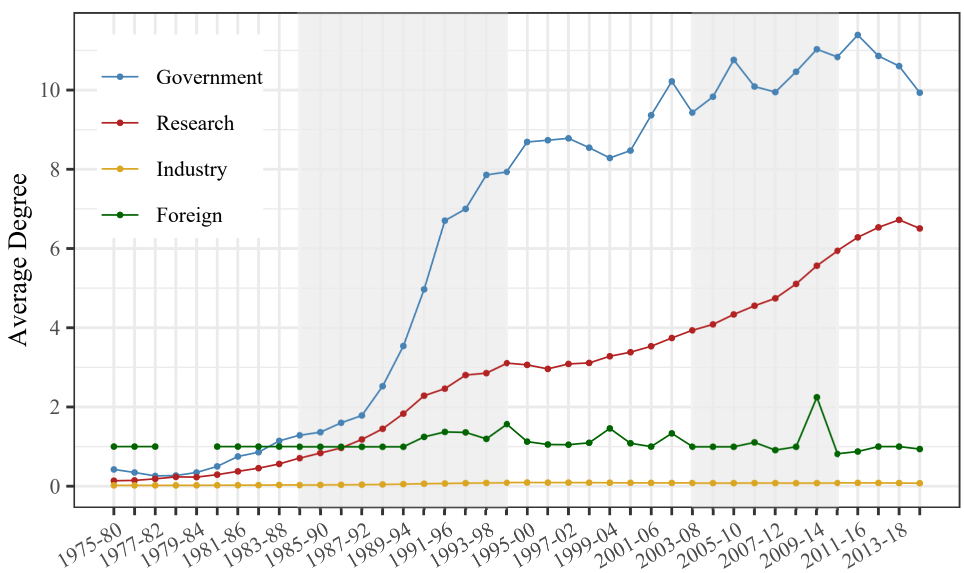
In both panels, government nodes sit on the top as the most connected (or central) set of nodes whether in the core or in the full network. Research nodes come second. To determine whether this ranking is statistically significant or not, however, one cannot make the normal distribution assumption. The main reason would be that the positional information in networks (such as centreality) are likely to exhibit structural correlations, owing to the co-evolvement of links (Dow et al., 1984; Krackhardt, 1988). I use the non-parametric Mann-Whitney test to check whether the averages are statistically different. The rankings stay by and large the same over time, therefore, I only report the statistics for 2014–19 in Table 2. As the table shows, the difference is not statistically significant. The small number of government nodes might be one reason for this insignificance.

The centerality changes over time. Inside the core, in particular, government's centrality jumps in the midst of wave 1. The centrality of research nodes increases in tandem but at a slower pace.

Post wave 1, the centrality of government within the core ebbs, though it keeps rising at a slower rate outside the core (panel (b)). By this time, the government appears to have given up its centralized efforts for collaboration building and, instead, is opting for localized ad hoc ties.



(a) Core



(b) Full Network

Figure 10: The average centrality of government, research, industry, and foreign nodes to the core and to the full network.

Industry and foreign nodes have the weakest positions, in the sense that they are the least connected. Even those located within the core have very few connections, positioning them at the perimeter. The significance tests in Table 2 confirm this inferior position for industry nodes. The tests for foreign nodes are mostly insignificant, owing to their small number.

The surge in government centrality during wave 1 is quite remarkable. A combination of forces and policy might have been behind this surge, chief among them the introduction of the National Cooperative Research Act (NCRA) of 1984 and the Federal Technology Transfer Act (FTTA) of 1986. The former was meant to remedy the declining productivity growth in manufacturing throughout 1970s and 80s by encouraging inter-organization research collaborations (Leyden &Link, 1999). The FFTA further paved the way by enabling FFRDCs to enter into cooperative research agreements with industrial firms. Accordingly, Leyden &Link (1999) find about 600 joint research ventures that have been registered in the wake of those acts, many of them involving FFRDCs.

The importance of FFRDCs in this phase is evident in a few trends. In Figure 11, I am showing the proportion of organizations affiliated with FFRDCs, either as a sponsor or an administrator, that are also core members.[5] The plot also shows the average degree of FFRDC-affiliated organizations, taken over all such organizations.

There is a rapid growth in the number of FFRDC-affiliated nodes in the core during wave 1. By the end of this wave, about 75 per cent of such agencies are in the core, up from 40 per cent at the start of the wave. Average degree for the affiliated organizations also grows sharply in tandem, moving them to central positions.

At the same time, these nodes almost wholly account for the surge in the centrality of government and research nodes during wave 1 (Figure 12). Centrality for government and research nodes not affiliated with any FFRDC grows only slightly in comparison.

FFRDCs also appear to be a major driving force during wave 2, albeit showing less energy. By this time, almost all FFRDC-affiliated organizations are already in the core. The centrality of government stagnates during this wave. On the other hand, the centrality of research nodes continues to grow, especially for those affiliated with FFRDCs (Figure 12).

I carry out a more rigorous examination of these changes by estimating a network re-

[5]For the list of FFRDCs and the sponsor or administering agencies, both current and historical, see NSF's master list.

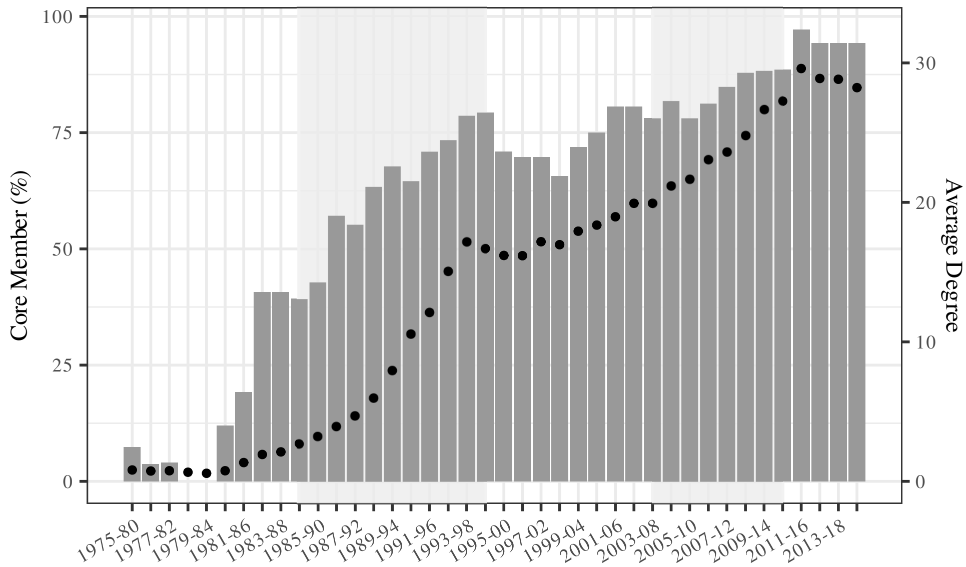


Figure 11: The proportion of FFRDC affiliates that are core members (bars), and the average degree of FFRDC affiliates in general (points).

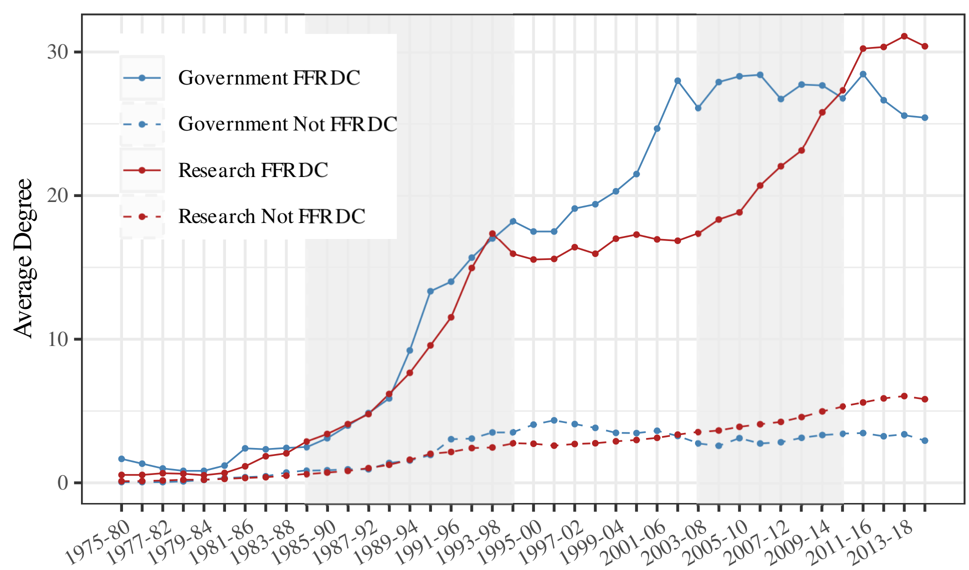


Figure 12: The degree centrality for government and research nodes sponsoring FFRDCS and those that do not.

gression for each wave. To use regression tools with networks, one only needs to imagine network statistics stacked as a vector, where row i corresponds to node i in the network and its characteristics. For my application, I use the following specification:

$$Degree_{it} = a_0 + a_1 Degree_{i,t-1} + G_i^{FFRDC} + R_i^{FFRDC} + G_i^{Other} + R_i^{Other} + \epsilon_{it}. \quad (3)$$

In the specification above, I am separating the role of government and research nodes with and without FFRDC affiliation (FFRDC or Other). Industry and foreign nodes are assigned as the base group (there are very few foreign nodes).

The specification also includes the node's degree in $t-1$ to shift the focus onto change in degree and not the degree itself. I carry out separate estimates of this model for each wave. For wave 1, the transition is from $t-1$ =1984–89 to t =1994–99. For wave 2, the transition is from $t-1$ =2003–08 to t =2010–15.

Model 3 can be estimated using the usual OLS method. However, as mentioned earlier, centrality measures might exhibit spacial correlations. Dow et al. (1984) propose incorporating a matrix of spatial weights akin to a spatial regression. For the case at hand, and to circumvent the problem of determining the unknown spatial weights, I conceptualize that the structural correlation should be the strongest in the core, and particularly around government and research nodes and those affiliated with FFRDCs. Based on this idea, I adjust standard errors by clustering noise by core membership, type of node and FFRDC affiliation.

Table 3 lists the estimated coefficients and their standard errors for each wave. As the table manifests, FFRDC-affiliated organizations tend to be more actively building ties than other organizations.

During wave 1, government and research nodes with FFRDC affiliation are particularly expanding their linkages at a fast rate. For a FFRDC government node, the degree grows by 10 above the average, whereas for a FFRDC university degree grows by 13 above the average. Without FFRDC affiliation, however, there is no significant growth in degree for government. Degree for research nodes without FFRDC affiliation grows by one and the statistical significance is weak.

The rate of growth in degree mostly dampens during wave 2. Government nodes affiliated with FFRDCs do not show a statistically significant change. However, there is a statistically

Variable	(1) Wave 1	(2) Wave 2	(3) Wave 1	(4) Wave 2
lag(Degree)	3.718***	1.359***	3.708***	1.350***
	(1.203)	(0.044)	(1.218)	(0.044)
G FFRDC	9.917***	−0.738	9.940***	−0.555
	(2.112)	(0.959)	(2.178)	(0.948)
R FFRDC	8.273***	3.764***	8.860***	3.406***
	(2.175)	(1.141)	(2.253)	(1.133)
G Other	0.294	0.409***	0.303	0.429***
	(0.909)	(0.144)	(0.917)	(0.152)
R Other	1.170*	0.665	1.127*	0.572
	(0.616)	(0.473)	(0.596)	(0.423)
R FFRDC Entrepreneurial			−5.380	5.405***
			(3.878)	(1.222)
R Other Entrepreneurial			3.357**	7.508***
			(1.425)	(1.231)
Adjusted R^2	0.540	0.886	0.542	0.888
F Statistic	10,146.3***	84,623.1***	7,295.0***	61,999.7***
N	43,150	54,565	43,150	54,565

Table 3: Factors affectign change in degree during each wave. ***, ** and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered by core membership, node type and FFRDC affiliation. G and R indicate government and research nodes. Industry and foreign nodes are assigned tas the base group.

significant increase in the centrality for other government nodes. This result conforms with the previous observations that suggested during wave 2 government was mostly building ties out of the core and not within.

Universities affiliated with FFRDCs are still expanding their ties during wave 2, but at a slower rate. This observation, again, mirrors those from Figures 10 and 12, which showed a steady but slow increase in centrality of universities with FFRDC affiliation.

The last finding is suggestive of the *second academic revolution* coming into full force, when universities added entrepreneurship and capitalization of innovation as their third mission besides teaching and research (Etzkowitz, 1998; Gulbrandsen & Slipersæter, 2007). For a closer look at this issue, I form an indicator of entrepreneurial university based on the listing provided by the Global League of Entrepreneurial Universites.[6]. In Appendix A, I list universities assigned as entrepreneurial in this analysis. Using these indicators, I carry out

[6]The list is available at `entrepreneurial-universities.org`. Last access for this reasearch was on March 20, 2024.

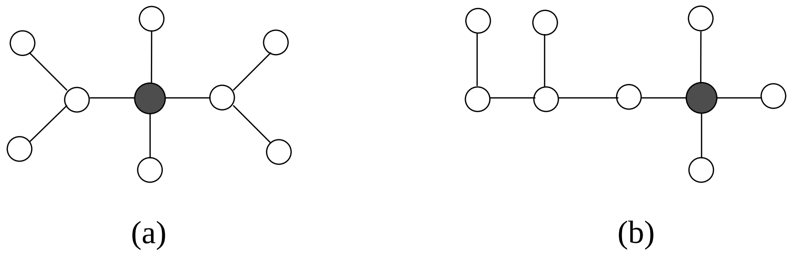


Figure 13: A simple example of closeness concept. The focal node (shown in black) has the same degree in networks (a) and (b). However, in network (a) it is closer to all other nodes.

two extra regressions. These estimations are listed in columns (3) and (4) of Table 3.

As these results show, entrepreneurial universities take a more active role during wave 2 in building ties. Even restricting to research nodes, entrepreneurial universities are still the most active. This feature was not as distinctive in wave 1. Judging based on the results, wave 2 is mostly defined by the reorientation of university activity towards entrepreneurship and flourishing of university–industry linkages.

5.2 Closeness

Closeness extends the concept of degree centrality by also accounting for nodes further down the path from a focal node. The concept is tightly related to knowledge diffusion. Proximity in social ties and institutional proximity are shown to be as potent as proximity in geography, if not more, in driving knowledge spillovers (Kirat & Lung, 1999; Breschi & Lissoni, 2005; Singh, 2005; Whittington et al., 2009).

Figure 13 is a simple depiction of the closeness concept. The focal node in both graphs has the same degree. In network (a), however, the focal point is at most two links away from the farthest node. In network (b), a number of nodes are three to four links away from the focal one. Access to and flow of knowledge through the focal node is, thus, better facilitated in network (a) than in network (b).

The closeness index quantifies this concept and, in its simplest form, is the reciprocal of the average geodesic distance, or the shortest path, from a node to every other node. If two nodes are disconnected, the geodesic distance between them is infinity. In such situation, simple averaging does not provide useful outcomes. Given the abundance of isolated nodes and disconnected sub-networks in the innovation network, I use the alternative definition from

Gil & Schmidt (1996). In this definition, instead of simple averaging, harmonic averaging is used. Formally:

$$Closeness_i = \frac{1}{N-1} \sum_{j \neq i} \frac{1}{d_{ij}}, \tag{4}$$

Where d_{ij} is the geodesic distance between nodes i and j. The index above takes a value between zero and one. For an isolated node, closeness is zero. For a node at the center of a star formation, with every other node one step away, the index is one.

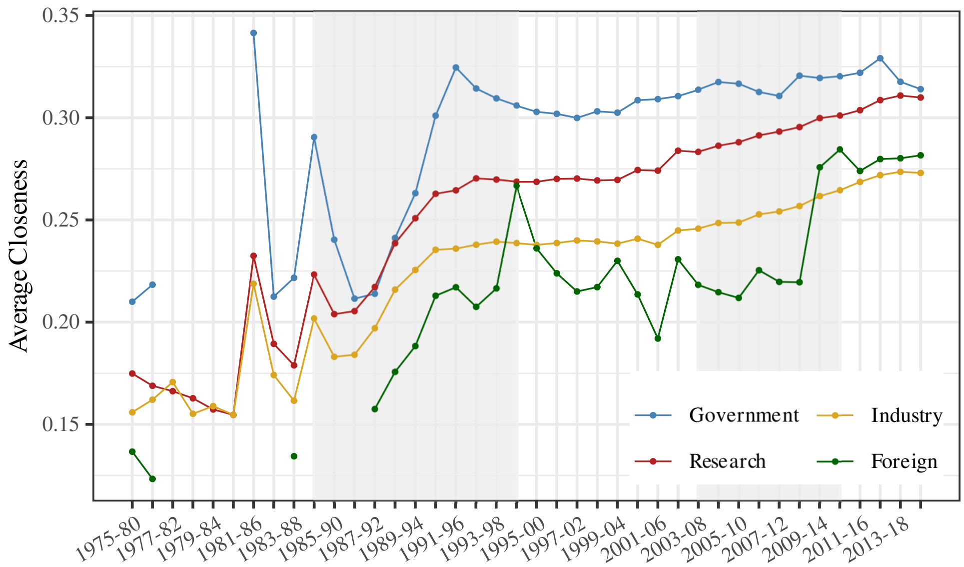
As with degree centrality, I compare the centrality of government, research, industry, and foreign nodes to the core and to the full network by averaging their closeness over the respective nodes. These averages are shown in Figure 14, where the top panel is averaging over nodes in the core and bottom panel averages over all nodes in the network.

The implications are almost similar to those with degree centrality. Government's closeness jumps with the onset of wave 1, then stays very much the same afterwards. Out of the core, however, government keeps getting closer to other nodes by forming localized networks.

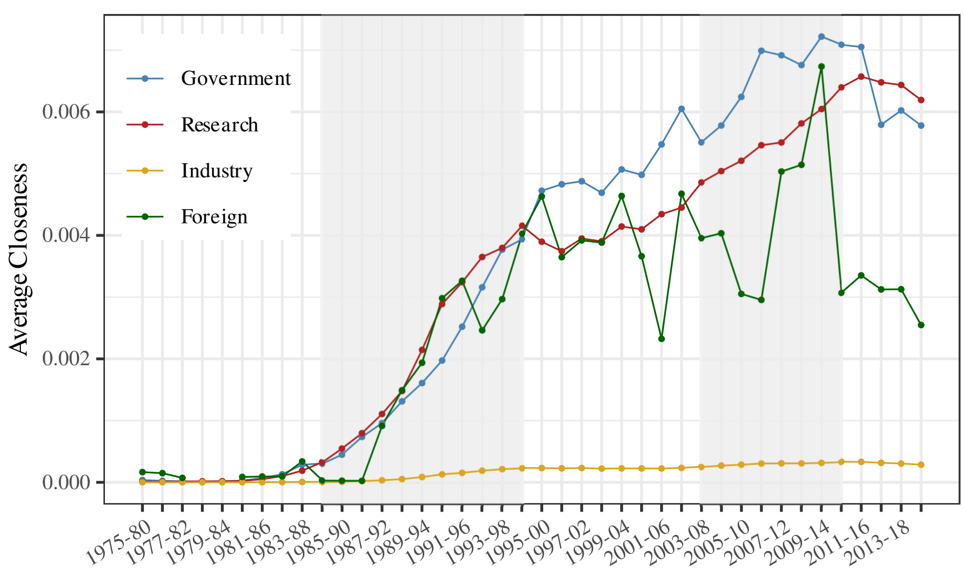
As for research nodes, they are constantly getting closer to other nodes both within and outside the core. The increase in their closeness accelerates during both waves 1 and 2. One difference from the degree centrality of the previous section is that government and research nodes are almost on par in closeness to other nodes. By 2014–19, both groups are on average about three links away (the reciprocal of closeness 0.3) from other core members.

The other difference concerns industry and foreign nodes. They still have lower centrality than government and research. Yet for those located within the core, they are approximately four links away from other nodes. Given these nodes have low degrees, the only conclusion is that, while sitting at the perimeter, they are connected to a central node. This way, the node is making pathways to other nodes through that focal connection.

The statistical significance of the differences in average closeness are listed in Table 4. The tests have the same pattern as with degree centrality. Specifically, the difference between government and research centrality is insignificant. The centrality of industry nodes is, however, significantly below that of other nodes. Differences with foreign nodes, again, do not show any significance due to the small number of foreign nodes.



(a) Core Closeness



(b) Full Network Closeness

Figure 14: The average closeness of government, research, and industry to the core and the full network.

Comparison			Network			Core		
			N_1	N_2	W	N_1	N_2	W
Foreign	>	Industry	56,734	16	82,679.5 [0.000]***	1,648	4	2,962.0 [0.729]
Research	>	Industry	56,734	719	9.06×10^6 [0.000]***	1,648	399	1.91×10^5 [0.000]***
Research	>	Foreign	719	16	5,196.0 [0.493]	399	4	521.5 [0.233]
Government	>	Research	45	719	15,433.0 [0.590]	23	399	4,636.5 [0.933]

Table 4: Mann–Whitney Rank test of difference in mean closeness centrality of different pairs of nodes in 2014–19. Numbers in brackets are p-values. *** denotes significance at 1% level.

6 Robustness Tests

6.1 Centrality by technology field

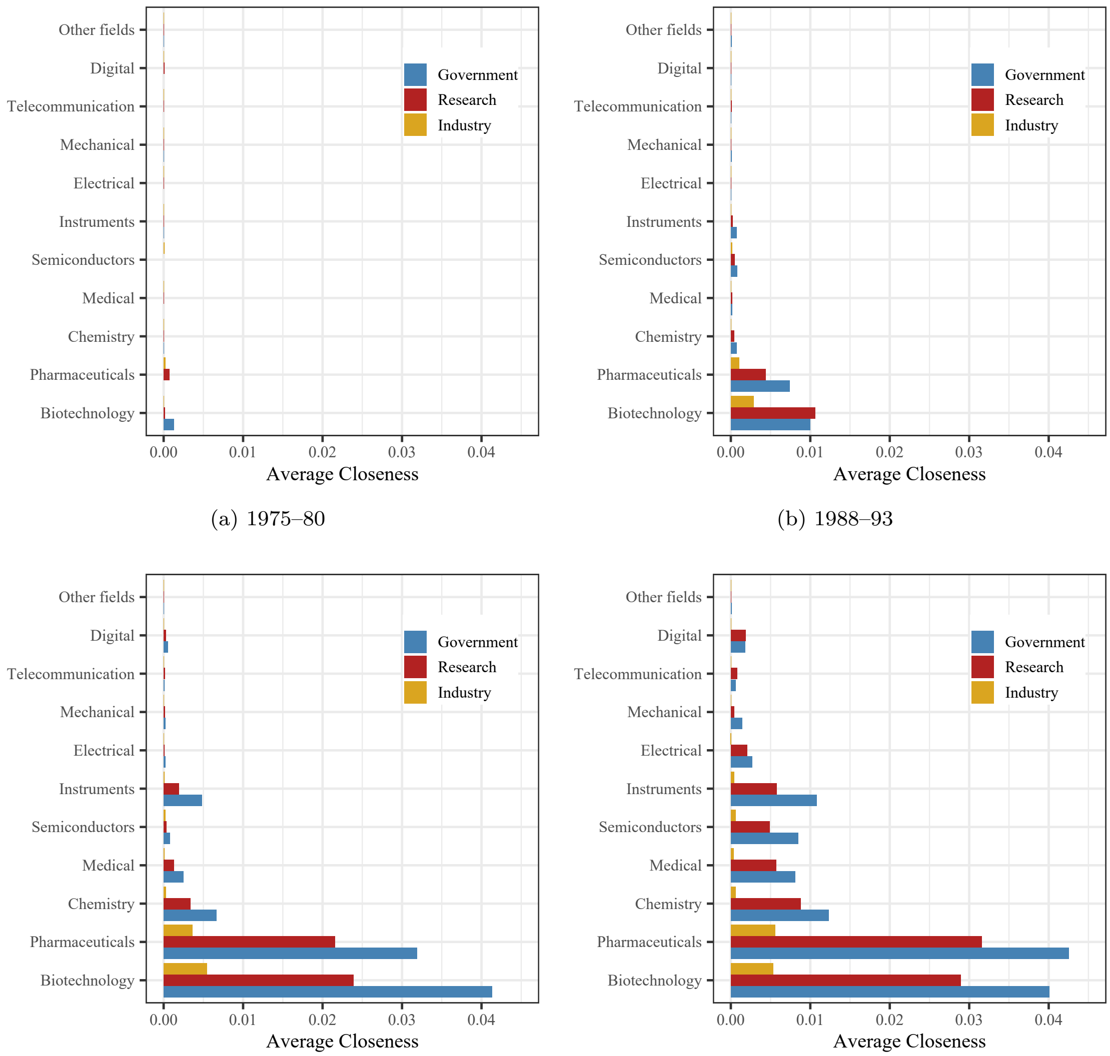
One critic that can be directed towards the results of the previous section is that universities are not one entity, but a collection of departments. Each department can be acting as a sole entity with little connection to other departments. The university's centrality aggregates these department-level centralities. Treating each department separately, however, could affect the centrality score of the research sector.

With a few exceptions, almost all patent assignees refer only to the university and not the department. Therefore, it is impractical to test whether the results are robust to the breaking down of universities into departments. The closest one can get to departments is to treat each technology class separately. In Figure 15, I illustrate the closeness centrality of different types of nodes by technology class and for four different periods.

The general implications from these pictures are the same as before. Specifically, Government nodes are the most central across very much every technology field. They are followed by research nodes as the second most central. The centrality of both government and research nodes rises over time in line with the waves of core expansion.

There is more. Government and research nodes are more central to certain technology fields. Biotechnology, Pharmaceuticals and Chemistry, in particular, benefit from a higher level of government and research centrality.

There are reasons why government's centrality is crucial to these technologies. Powell et



(a) 1975–80

(b) 1988–93

(c) 2001–06

(d) 2014–19

Figure 15: Average centrality of government, research and industry in different technology areas.

al. (1996) argue that technologies for which knowledge base is complex and fast expanding and that knowledge is dispersed across many organizations, there is an inherent push for firms to seek collaboration. In this network, organizations with deeper and more diverse knowledge, e.g. government research centers and universities, expand their contacts faster than others and assume the central positions. Kirat & Lung (1999) specially argue in favor of institutional proximity as an important factor driving innovation in knowledge-intensive technologies.

Another point to draw from Figure 15 is that the centrality of government and research nodes expands in tandem with the expansion of the network itself to encompass a wider range of technologies. In the early periods, the centrality of government and research nodes was mostly limited to the areas mentioned above. In the later periods, however, these nodes become quite central to areas such as Instruments, Medical, and Semiconductor technologies.

6.2 Centrality of large firms

Another way to look at the issue raise in the last section is to compare universities with large corporations. In large corporations, similar to universities, there are many divisions that could be far apart. As a result, these corporation behave somewhat like a university with multiple departments.

I recompute the average closeness index for each type of node but only including nodes that have at least 100 patents, on average, per period. The results are shown in Figure 16 and show the same ranking as before.

7 Conclusion

Apart from advancing knowledge and science, research centers run by government and universities also bridge other innovators and facilitate knowledge exchange between them and further around the network. The social and human capital of the whole network largely depends on the stock of knowledge these centers embody and also from their ability to absorb, compile and disseminate knowledge. In such a setting, innovations come more frequently and have a higher value for drawing on a larger pool of expertise. At the same time, the focus by

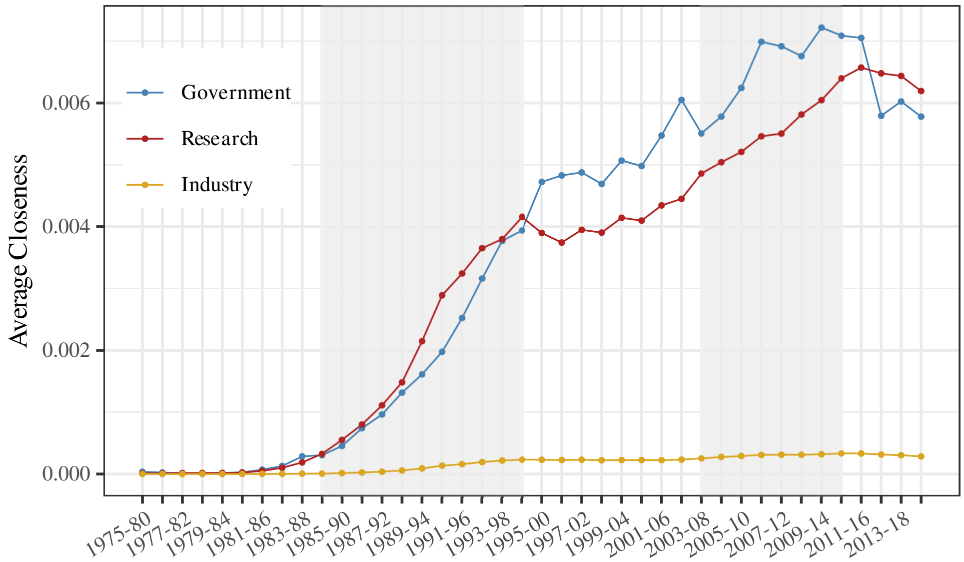


Figure 16: The average closeness for government, research and industry nodes. Including only nodes that have at least 100 patents, on average, per period.

the US government on market solutions to encourage innovations and the obscurity of non-market solutions in its policies raised concerns that the US innovation ecosystem might be missing an important actor. The findings of this paper show that although the government had very little centrality back in 1970s, its centrality grew substantially, with the onset of Federal Technology Transfer Act in 1986. Two waves of increasing government and university engagement with industrial firms are evident in the data. FFRDCs are the main force in each case and reach out for more industry involvement. In the early stage, the core of collaboration forms as a result and expands rapidly. Meanwhile, government and research organizations affiliated with FFRDCs are thrust into network's central positions. A second wave follows during the 2000s. Unlike the first wave, this one is more about the flourishing of university–industry collaborations and leads to the rise of *entrepreneurial universities*.

The collaborations between government, research organizations and industry encompass every field of technology but to vastly different extents. Where the technology is more complex and knowledge and expertise is more dispersed, namely, chemistry, biotechnology and pharmaceuticals, the industry's appetite for collaboration is great. Government and research organizations hold their most central positions within these technologies. In the recent years, government and research organizations have also diversified their presence and gained centrality in other fields, most notably in medical, instrument and semiconductor technologies. The way these collaborations are evolving suggests the trend will continue with universities probably taking an increasingly central role across a wider range of technologies.

Observing the formation and evolution of the collaboration network has a few lessons that can go beyond the US context. Basic research and complex innovations contribute to long-term productivity growth. Offering research grants and tax subsidies is an ineffective approach to boosting basic research, as they are mostly directed to applied and experimental development (OECD, 2023). To push for basic and complex innovations, networks of collaboration are needed, and large networks of collaboration only materialize when the government assumes a certain level of centrality. Such policy puts government's intramural research in focus as a key factor, not to crowd out private research, but to promote collaboration and basic innovation.

Appendix

A Entrepreneurial Universities

Below is the list of US universities listed as entreprteneurial. There are a few liberal arts colleges, such as Babson College and Flagler College, also listed as being entrepreneurial. However, these colleges have not registered any patents, therefore, do not show up in the patent data and the network.

- Arizona State University
- Carnegie Mellon University
- Chicago State University
- Florida State University
- Indiana University
- Lawrence Technological University
- Massachusetts Institute Of Technology
- Northeastern University
- Stanford University

- Syracuse University
- University Of Colorado
- University of California, Berkeley
- University of Houston
- University Of Louisville
- University of North Carolina, Chapel Hill
- West Virginia University

References

Acs, Zoltan J., David B. Audretsch, Erk E. Lehmann (2017) "National Systems of Innovation," *Journal of Technology Transfer*, 42(5), 997–1008.

Aram, John D., Leonard H. Lynn, and N Mohan Reddy (1992) "Institutional Relationships and Technology Commercialization: Limitations of Market Based Policy," *Research Policy*, 21(5), 409–421.

Bakhtiari, Sasan (2023) "Growing by Outsourcing: a Tale of Two Growths," *Empirica*, 50(2), 411–439.

Batagelj, Vladimir, and Matevz Bren (1995) "Comparing Resemblance Measures," *Journal of Classification*, 12(1), 73–90.

Baum, Joel A., Tony Calabrese, and Brian S. Silverman (2000) "Don't Go it Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology," *Strategic Management Journal*, 21(3), 267–294.

Boschma, Ron A., and Anne L. J. Ter Wal (2007) "Knowledge Networks and Innovative Performance in an Industrial District: The Case of a Footwear District in the South of Italy," *Industry and Innovation*, 14(2), 177–199.

Bramoullé, Yann, Rachel Kranton, and Martin D'Amours (2014) "Strategic Interaction and Networks," *American Economic Review*, 104(3), 898–930.

Breschi, Stefano, and Francesco Lissoni (2003) "Mobility and Social Networks: Localised Knowledge Spillovers Revisited, Centre for European Economic Research (ZEW).

Breunig, Robert V., and Sasan Bakhtiari (2013) "Outsourcing and Innovation: An Empirical Exploration of the Dynamic Relationship," *B.E. Journal of Economic Analysis and Policy*, 13(1), 395–418.

Browning, Larry D., Janice M. Beyer, and Judy C. Shetler (1995) "Building Cooperation in a Competitive Industry: SEMATECH and the Semiconductor Industry," *Academy of Management Journal*, 38(1), 113–151.

Burt, Ronald S. (2004) "Structural Holes and Good Ideas," *American Journal of Sociology*, 110(2), 349–399.

Cantner, Uwe, Holger Graf (2006) "The Network of Innovators in Jena: An Application of Social Network Analysis," *Research Policy*, 35(4), 463–480.

Ciszewska-Mlinarič, Mariola, and Aleksandra Wasowska (2015) *Resource-Based View (RBV)*," Wiley Encyclopedia of Management, Volume 6: International Management, Edited by Cary L. Cooper, John Wiley and Sons, London.

Cohen, Wesley M., and Daniel A. Levinthal (1990) "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly*, 35(1), 397–422.

Cohen, Wesley M., Richard R. Nelson, and John P. Walsh (2002) "Links and Impacts: The Influence of Public Research on Industrial R&D," *Management Science*, 48(1), 1–23.

CBO (2021) "Research and Development in the Pharmaceutical Industry," Congressional Budget Office, Publication 57025.

Dahl, Michael S., and Christian Ø.R. Pedersen (2004) "Knowledge Flows Through Informal Contacts in Industrial Clusters: Myth or Reality?" *Research Policy*, 33(10), 1673–1686.

Dasaratha, Krishna (2023) "Innovation and Strategic Network Formation," *Review of Economic Studies*, 90(1), 229-–260.

Dow, Malcolm M., Michael L. Burton, Douglas R. White, and Karl P. Reitz (1984) "Galton's Problem as Network Autocorrelation," *American Ethnologist*, 11(4), 754–770.

Etzkowitz, Henry (1998) "The Norms of Entrepreneurial Science: Cognitive Effects of the New University–Industry Linkages," *Research Policy*, 27(8), 823–833.

Fleming, Lee, H. Greene, G. Li, M. Marx, and D. Yao (2019) "Government-funded Research Increasingly Fuels Innovation," *Science*, 364(6446), 1139–1141.

Geletkanycz, Marta A., and Donald C. Hambrick (1997) "The External Ties of Top Executives: Implications for Strategic Choice and Performance," *Administrative Science Quarterly*, 42(4), 654–81.

Gil-Mendieta, Jorge, and Samuel Schmidt (1996) "The origin of the Mexican network of power," *International Social Network Conference*, Charleston, S.C., USA, 22–25.

Giuliani, Elisa, and Martin Bell (2005) "The Micro-determinants of Meso-level Learning and Innovation: Evidence from a Chilean Wine Cluster," *Research Policy*, 34(1), 47–68. Massachusetts, 25-–56

Gulati, Ranjay (1998) "Alliances and Networks," *Strategic Management Journal*, 19(4), 293–317.

Gulati, Ranjay (1999) "Network Location and Learning: The Influence of Network Resources and Firm Capabilities on Alliance Formation," *Strategic Management Journal*, 20(5), 397–420.

Gulati, Ranjay, Nitin Nohria, and Akbar Zaheer (2000) "Strategic Networks," *Strategic Management Journal*, 21(3), 203–215.

Gulbrandsen, Magnus, and Stig Slipersæter (2007) "The Third Mission and the Entrepreneurial University Model," *Universities and Strategic Knowledge Creation: Specialization and Performance in Europe*, edited by Andrea Bonaccorsi and Cinzia Daraio, Edward Elgar, Cheltenham, 112–143.

Hagedoorn, John (2002) "Inter-firm R&D Partnerships: an Overview of Major Trends and Patterns since 1960," *Research Policy*, 31(4), 477–492.

Hagedoorn, John (2003) "Sharing Intellectual Property Rights – an Exploratory Study of Joint Patenting amongst Companies," *Industrial and Corporate Change*, 12(5), 1035–1050.

Hansen, Morten T. (1999) "The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge across Organization Subunits," *Administrative Science Quarterly*, 44(1), 82–111.

Howells, Jeremy (2006) "Intermediation and the role of intermediaries in innovation," *Research Policy*, 35(5), 715–728.

Hunter, David R., Mark S. Handcock, Carter T. Butts, Steven M. Goodreau, and Martina Morris (2008) "ERGM: A Package to Fit, Simulate and Diagnose Exponential-Family Models for Networks," *Journal of Statistical Software* 24(3), 1–29.

Jaffe, Adam B., Michael S. Fogarty, and Bruce A. Banks (1998) "Evidence from Patents and Patent Citations on the Impact of NASA and other Federal Labs on Commercial Innovation," *Journal of Industrial Economics*, 46(2), 183–205.

Kirat, Thierry, and Yannick Lung (1999) "Innovation and Proximity: Territories as Loci of Collective Learning Processes," *European Urban and Regional Studies*, 6(1), 27–38.

Kogut, Bruce (1989) "The Stability of Joint Ventures: Reciprocity and Competitive Rivalry," *Journal of Industrial Economics*, 38(2), 183–198.

Krackhardt, David (1988) "Predicting with Networks: Nonparametric Multiple Regression Analysis of Dyadic Data," *Social Networks*, 10(4), 359–381.

Leyden, Dennis P. , and Albert N. Link (1999) "Federal Laboratories as Research Partners," *International Journal of Industrial Organization*, 17(4), 575–592.

Lynn, Leonard H., N. Mohan Reddy, and John D. Aram (1996) "Linking Technology and Institutions: the Innovation Community Framework," *Research Policy*, 25(1), 91–106.

Majeed, Omer and Robert Breunig (2023) "Determinants of Innovation Novelty: Evidence from Australian Administrative Data," *Economics of Innovation and New Technology*, 32(8), 1249–1273.

McEvily, Bill, and Akbar Zaheer (1999) "Bridging Ties: A Source of Firm Heterogeneity in Competitive Capabilities," *Strategic Management Journal*, 20(12), 1133-1156.

Miotti, Luis, and Frédérique Sachwald (2003) "Co-operative R&D: why and with whom?: An integrated framework of analysis," *Research Policy*, 32(8), 1481–1499.

Mitre (2015) "A Primer: Federally Funded Research and Development Centers in the 21st Century," *Mitre Corporation*.

Nelson, Richard R. (1993) *National Systems of Innovation: A Comparative Analysis*, Oxford University Press, New York.

Newman, Mark E. J. (2003) "The Structure and Function of Complex Networks," *SIAM Review*, 45(2), 167–256.

OECD (2023) "The Impact of R&D tax incentives ," *OECD Publishing*, Paper No.159.

Oxley, Joanne E. (1997) "Appropriability Hazards and Governance in Strategic Alliances: A Transaction Cost Approach, *Journal of Law, Economics, and Organization*, 13(2), 387–409.

Podolny, Joel M. and Toby E. Stuart (1995) "A Role-based Ecology of Technological Change," *American Journal of Sociology*, 100(5), 1224–1260.

Podolny, Joel M. and Karen L. Page (1998) "Network Forms of Organization," *Annual Review of Sociology*, 24(1), 57–76.

Powell, Walter W. (1990) "Neither Market nor Hierarchy: Network Forms of Organization," *Research in Organizational Behavior*, 12, 295–336.

Powell, Walter W., Kenneth W. Koput, and Laurel Smith-Doerr (1996) "Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology," *Administrative Science Quarterly*, 41(1), 116–145.

Rangan, Subramanian (2000) "The Problem of Search and Deliberation in Economic Action: When Social Networks Really Matter," *Academy of Management Review*, 25(4), 813–838.

Reuer, Jeffrey J., Nandini Lahiri (2014) "Searching for Alliance Partners: Effects of Geographic Distance on the Formation of R&D Collaborations," *Organization Science*, 25(1), 283–298.

Rosenberg, Nathan (1990) "Why Do Firms Do Basic Research (With Their Own Money)?" *Research Policy*, 19(2), 165–174.

Sampson, Rachelle C. (2004) "The Cost of Misaligned Governance in R&D Alliances," *Journal of Law, Economics, and Organization*, 20(2), 484–526.

Schmoch, Ulrich (2008) "Concept of a Technology Classification for Country Comparison," *World Intellectual Property Organization*, IPC/CE/41/5, Annex 1.

Shan, Weijan, Gordon Walker, and Bruce Kogut (1994) "Interfirm Cooperation and Startup Innovation in the Biotechnology Industry," *Strategic Management Journal*, 15(5), 387–394.

Shohet, Simon, and Martha Prevezer (1996) "UK Biotechnology: Institutional Linkages, Technology Transfer and the Role of Intermediaries," *R&D Managament*, 26(3), 283–298.

Shokouhmand, Arash, Haoran Wen, Samiha Khan, Joseph A. Puma, Amisha Patel, Philip Green, Farrokh Ayazi, and Negar Ebadi (2023) "Diagnosis of Coexisting Valvular Heart Diseases Using Image-to-Sequence Translation of Contact Microphone Recordings," *IEEE Transactions on Biomedical Engineering*, 70(9), 2540–2551.

Singh, Jasjit (2005) "Collaborative Networks as Determinants of Knowledge Diffusion Patterns," *Management Science*, 51(5), 679-849.

Smith-Doer, Laurel, and Walter W. Powell (2005) "Networks and Economic Life," Chapter 17 in the *Handbook of Economic Sociology*, Edited by Smith-Doer, Powell, Swedberg, and Smelser, Princeton University Press, Princeton.

Snijder, Tom A.B., Gerhard G. van de Bunt, and Chritian E.G. Steglich (2010) "Introduction to Stochastic Actor-based Models for Network Dynamics," *Social Networks*, 32(1), 44–60.

Stuart, Toby E. (2000) "Interorganizational Alliances and the Performance of Firms: a Study of Growth and Innovation Rates in a High-technology Industry," *Strategic Management Journal*, 21(8), 791–811.

Tsai, Wenpin (2001) "Knowledge Transfer in Intraorganizational Networks: Effects of Network Position and Absorptive Capacity on Business Unit Innovation and Performance," *Academy of Management Journal*, 44(5), 996–1004.

Villani, Elisa, Einar Rasmussen, and Rosa Grimaldi (2017) "How intermediary organizations facilitate university–industry technology transfer: A proximity approach," *Technological Forecasting and Social Change*, 114(1), 86–102.

Whittington, Kiersten B., Jason Owen-Smith, and Walter W. Powell (2009) "Networks, Propinquity, and Innovation in Knowledge-Intensive Industries," *Administrative Science Quarterly*, 54(1), 90–122.