



Structure of university licensing networks

Dolores Modic^{1,2,3} · Borut Lužar²  · Tohru Yoshioka-Kobayashi⁴

Received: 4 December 2021 / Accepted: 12 October 2022 / Published online: 30 November 2022
© The Author(s) 2022

Abstract

We study the structure and evolution of networks of inventors involved in university licensing and patenting. In particular, we focus on networks of inventors that have successfully licensed a university patent (i.e., *licensing networks*), and investigate levels of their fragmentation, cliquishness, and whether they exhibit the small world phenomenon. We find that these licensing networks are more fragmented and cliquish than the networks of inventors engaged in all (not necessarily licensed) patents (i.e., *patenting networks*), and that they are not small worlds. Additionally, by comparing the created licensing networks to random subnetworks of the patenting networks, we find that concerns in regard to the potential effects of opportunistic behavior are, to some degree, justified. We detect an interesting collaboration behavior of inventors who license, which we designate as dualistic opportunistic behavior.

Keywords Social network analysis · Patenting network · Licensing network · University commercialization · Technology Transfer

Introduction

The third mission of universities, i.e., embracing the mission of economic development alongside teaching and research roles (Etzkowitz & Leydesdorff, 2000), is tightly connected to the commercialization of university inventions and technology transfer (Berghaeuser & Hoelscher, 2020; Cesaroni & Piccaluga, 2016). This topic has received significant attention in the media and is of high priority in policy agendas (Bercovitz & Feldman, 2006; Zhao

✉ Dolores Modic
dolores.modic@nord.no

Borut Lužar
borut.luzar@gmail.com

Tohru Yoshioka-Kobayashi
t-koba@iir.hit-u.ac.jp

¹ Nord University Business School, Bodø, Norway

² Faculty of Information Studies in Novo Mesto, Novo Mesto, Slovenia

³ Rudolfovo, Science and Technology Centre, Novo Mesto, Slovenia

⁴ Institute of Innovation Research, Hitotsubashi University, Tokyo, Japan

et al., 2020). The emphasis on commercialization efforts exists against the backdrop of the academic tradition of knowledge sharing and funding programs encouraging collaboration (Dasgupta & David, 1994; Nelson, 2004; Walsh et al., 2007). To understand collaborative relationships, including in innovation, social network studies have been helpful (see, e.g., Prell, 2012). Notwithstanding the attention to social networks, our knowledge of the patenting and licensing networks' properties remains limited. We also know little about whether and how dealing with university inventions with high commercialization potential, i.e., those that are licensed, moderates the social networks' properties.

A network structure plays an important role in innovation activities (e.g., Casper, 2013; Fleming et al., 2007; Schilling & Phelps, 2007; Tahmoonesnejad & Beaudry, 2018). In innovation, a myriad of studies investigated different properties of social networks (e.g., Cassi & Plunket, 2015; Fleming et al., 2007; He & Fallah, 2009; Schilling & Phelps, 2007; Uzzi & Spiro, 2005), including their fragmentation, cliquishness, and whether they are small worlds. Prior research on social networks related to patenting revealed that they can be relatively fragmented, and substantially more fragmented than those within open science (Breschi & Catalini, 2010; Lissoni et al., 2013). In social network studies, it is also common to discover cliquishness (e.g., Beaudry & Kananian, 2013; He & Fallah, 2009; Schilling & Phelps, 2007) and a small world network structure (e.g., Fleming et al., 2007; Uzzi & Spiro, 2005); but the latter remains somewhat unclear in terms of patenting (Balconi et al., 2004; Lissoni et al., 2013).

Only few studies focusing specifically on licensing networks have been performed, and these have been done either at inter-organizational (Hu & Zhang, 2021) or inter-regional level (Yang et al., 2021b). Moreover, studies focusing on relationships between individual researchers have not explored questions related to structure of the licensing networks (Kotha et al., 2013). The question of which properties licensing networks at university level would display, thus remains unanswered. This paucity of research dealing is likely due to a lack of available data (Bercovitz et al., 2019; Wright et al., 2014). Since licensing is a result of relationships on individual level, insights brought by research on interpersonal level can be especially informative, and can help build both policy and organizational level recommendations.

Actors' choice to invest or not to invest in their ties and actions can have consequences for the structure of their social networks (Gulati et al., 2012; Prell, 2009). In this line, recent social network studies began to focus on the opportunistic behavior of actors and its consequences on the network structure. For example, a firm's competitive advantage seeking behavior often drive them into a structural hole position and, simultaneously, expand their affiliated networks (Guo et al., 2021). Consequently, such behavior can lead to diverse network structures (Guo et al., 2021).

However, we do not know how dealing with university inventions with high commercialization potential, i.e., those that are licensed, moderates the social networks' properties. But such understanding can be very relevant, since from a commercial value perspective, licensed patents are more relevant for the industry (Kotha et al., 2013), which brings to the forefront the focus on the inventions with the highest commercial potential. When inventors and technology licensing offices deal with patents with the most commercialization potential, their respective collaboration patterns can differ from their overall patterns, due to the inventors' behavioral change (Blumenthal et al., 1997). It is possible that opportunity assessment causes opportunistic behavior (Das & Rahman, 2010; Haeussler, 2011; Williamson, 1985) mirrored in changed formation of social ties, which in turn affect the properties of the licensing networks.

To reveal the nature of collaboration in academic commercialization, we explored networks of inventors involved in licensing. At the core of our research lies the question of whether the engagement of inventors in patents with the most potential for commercialization (i.e., the licensed patents) affects the properties of their respective licensing networks in terms of fragmentation, cliquishness and small worlds. For such networks, the intuitive answer to our question would be affirmative. Nonetheless, there is still ambiguity in both theory and empirical evidence. The question is an especially interesting one in settings, such as universities, where potential opportunistic behaviors based on higher recognition of potential are being countered by Mertonian norms encouraging collaboration. Ideal Mertonian norms emphasizing revealing and sharing scientific resources and knowledge (Merton, 1957), and the general benefits deriving from collaboration (Bozeman & Corley, 2004), could counter-measure substantial negative effects potentially caused by opportunistic behavior related to university inventions with high potential. This makes studying social networks in a university setting especially salient; and can give us hints as to how successfully building up the environments that value collaboration can counter the effects of opportunistic behaviors.

We investigate the network properties of licensing networks at two focal universities, and compare them first to the patenting networks inside these same universities. Next, we test whether licensing networks exhibit unexpected network properties by comparing them to a sample of random subnetworks of the patenting networks. Our analysis allows us to highlight some unexpected properties of licensing networks, such as the lack of small worlds, and that in some cases fragmentation can be so high that a significant size giant component, i.e., large component of connected network members, does not even appear. Both are unusual phenomena in social networks, especially for environments that in general value collaboration. Combining the analysis of network properties and micro-level insights, we also detect some interesting collaboration behaviors of inventors who license, which we term as dualistic behavior.

In contrast to previous studies, we use an original dataset of technology transfer administrative data from two Japanese universities. The dataset includes more than 9000 inventors active between 2004 and 2014. A distinguishing aspect of our research is our multi-level and temporal network analysis on novel, hard-to-obtain licensing datasets. By doing so, we add to the broader discussion of the potential opportunity-recognition effects on social networks' properties by bringing licensing networks to the forefront. Much of the previous literature dedicated to the study of networks in university settings was particularly interested in exploring knowledge spillovers or consequences of collaborations, leaving a knowledge gap in the literature related to exploring the intrinsic properties of these networks (Boschma & Frenken, 2009; Crescenzi et al., 2016).

Social networks properties in the university commercialization context

Social network properties: network fragmentation, cliquishness, and small worlds

Exploring structural properties of social networks is of key importance, since the structure of networks can influence how knowledge is combined (Yayavaram & Ahuja, 2008), and can have effects on innovation activities. For example, studies showed that a less fragmented regional academics' co-inventor networks are associated with high science-based innovations (Casper, 2013). It was also shown previously that a high network centrality of

researchers is connected to high productivity in patenting (Tahmooresnejad & Beaudry, 2018).

Several network properties are commonly explored in social network research, such as centralization, density, network diameter and average path lengths, as well as cliquishness, fragmentation, and small worlds (Prell, 2012). We chose to focus on the latter three properties. We do so, since ‘cliquish’ networks can increase the level of trust among individuals, encourage sharing of knowledge, and stimulate engagement in joint activities (Cassi & Plunket, 2015; Coleman, 1988). Once such cliquish networks interconnect with each other, even though sparsely, i.e., typically form a ‘small world’ network, ideas and knowledge can flow to diversified actors (Uzzi & Spiro, 2005). However, not all networks interconnect, some remain fragmented (Balconi et al., 2004; Lissoni et al., 2013).

We first focus on cliquishness. Collaborating researchers typically comprise groups wherein knowledge and ideas are easily transferred between members (Perry-Smith & Shalley, 2003). Many researchers tend to work with the people in their own group (Bozeman & Corley, 2004) and most ties between inventors re-affirm already existing collaborations (Forti et al., 2013). In line with the closure argument (Coleman, 1988), social network studies often capture ‘cliquishness’ in networks (e.g., Beaudry & Kananian, 2013; He & Fallah, 2009), mirrored in networks of densely connected groups. Frequent and redundant connections increase the fine-grained information exchange which is timely, accurate and of high quality, formulate common language and communication codes, promote trust and learning between researchers, and therefore deepen their collaboration (Beaudry & Kananian, 2013; Breschi & Catalini, 2010; Forti et al., 2013; Prell, 2009).

However, membership in highly connected networks can also limit the range of activities and may limit the access to non-redundant knowledge. Based on Burt’s (2005) work, non-redundant knowledge sharing is important, and building networks with large numbers of indirect ties may be an effective way for actors to enjoy the benefits of network size without the costs of network maintenance associated with direct ties. Consequently, it is important for group members to reach beyond the borders of their original groups, since these external relationships can bring in non-redundant knowledge. Two inventors with common co-workers can influence each other even if they have never collaborated directly (Brown & Duguid, 2001), and both direct and indirect ties can matter, not only for exploration, but also for exploitation of knowledge (Ahuja, 2000; Guan & Liu, 2016).

Thus, apart from investigating the level to which individual researchers are interconnected, we also turn to exploring how well the researchers in the network are connected globally, i.e., to network fragmentation. Many obstacles, such as coordination costs, institutional contexts, or incentive mechanisms (Landry & Amara, 1998), prevent individual actors from collaborating beyond their boundaries. Consequently, the vast majority of networks have isolated subnetworks (e.g., Forti et al., 2013). Nonetheless, by connecting beyond boundaries, actors can potentially gain a great deal, including new information and opportunities, new resources, and new ideas for solving problems (Granovetter, 1973; Lin, 2001).

But although parts of collaboration networks can remain closed for new members, long periods some boundary spanners can exist between densely connected groups (Breschi & Catalini, 2010). These are relatively rare people who link distinct groups and contribute to establishing relationships between multiple, otherwise cliquish, groups. The essence of small world structure is the linkage of densely connected groups by the boundary spanners; as Fleming and Marx (2006) point out, isolated clusters or an overabundance of ties between unclustered inventors are not small worlds. A small world network structure has been frequently detected (e.g., Fleming et al., 2007; Uzzi & Spiro, 2005), including in

some research focusing on patenting networks, such as those related to patenting in nano-technology (Guan & Shi, 2012) or in communication technologies (Hung & Wang, 2010). Lissoni et al., (2013: 197) point out, that “small world structures are apt to ensure fast and widespread diffusion of technical and scientific knowledge”, which is an important feature in university commercialization networks.

Social networks in university commercialization

Studying networks allows us to gain insight into goal-oriented collaborations which require knowledge sharing. Particularly, the university inventions are commonly a result of such goal-oriented collaborations between inventors (Bercovitz & Feldman, 2010; Kotha et al., 2013; Wuchty et al., 2007). Social network analysis encompassing university researchers primarily focuses on the collaborative nature of researchers by studying large networks of co-authorships (Newman & Girvan, 2004; Tu, 2019; Wang, 2016) and (to a lesser degree) co-inventorships, seldom combining co-authorship and co-inventorship (Breschi & Catalini, 2010; Cattani & Rotolo, 2014; Subramanian et al., 2013).

Research on co-inventorships typically explores patenting networks (Balconi et al., 2004; Crescenzi et al., 2017; De Prato & Nepelski, 2014; Forti et al., 2013; Guan & Liu, 2016; Huggins et al., 2020; Hur & Park, 2016; Lissoni et al., 2013; Morescalchi et al., 2015; Yang et al., 2021a). The use of social network theories and methods on patenting data has already resulted in significant contributions; from those related to the determinants of network properties (e.g., Forti et al., 2013; Huggins et al., 2020; Morescalchi et al., 2015; Yang et al., 2021a) to those related the effect of networks on innovation performance (e.g., Guan & Liu, 2016; Hur & Park, 2016).

However, when combined with a focus on universities, and with what Phelps et al. (2012) call interpersonal level, i.e., studies with the focus on individuals and the relationships among them, research has rarely been dedicated to studying network properties. The research done in relation to patenting networks is usually limited to a particular field (Breschi & Catalini, 2010; Guan & Liu, 2016), or a region or country (Balconi et al., 2004; Lissoni et al., 2013; Morescalchi et al., 2015), thus not providing a university-level perspective. As opposed to the extant literature, we did not limit this research to a particular field, but observed the properties of social networks in patenting and licensing at two focal universities with specific regard to licensing. This is especially relevant, since one of the challenges in researching both patenting and licensing are the scientific competition effects, which are a major cause of science fragmentation within a discipline (Hong & Walsh, 2009). Our approach allows us to control for these influences. Next, exploring licensing on the university level can give us a more complete picture than using registry data on the regional or national level, since the registration of licensing is typically recorded on a voluntary basis and typically does not adequately present all licensing activities (Yang et al., 2021b; Ye et al., 2020).

There are few studies that focus at least partially on licensing networks. Hu and Zhang (2021) recently engaged in a spatial–temporal analysis of assigned patents of U.S. universities, however, their focus remained on collaboration between organizations. Yang et al. (2021b) used a voluntary Chinese licensing database, but their focus remained on inter-regional aspects. Kotha et al. (2013) dealt with inventors that co-invented a licensed patent, however, they did not examine the properties of these networks. They rather explored the role of within-group collaboration experience as a moderator of coordination costs that could potentially affect the licensing likelihood. Hence,

the literature focusing on licensing does not provide us insights into the structures of licensing networks.

In terms of fragmentation in a university environment, we know more about co-authorship networks, whereas our understanding of fragmentation in patenting remains limited. Many researchers, in order to provide evidence on the existence of fragmentation or lack thereof, observed so-called giant components in networks (Velden et al., 2010). With regard to co-authorship networks, most evidence shows that their giant components are comprised of more than 80% of nodes and thus strong fragmentation does not appear: for example, 88% of nodes in the Pakistani chemistry researcher network (Badar et al., 2013) and 80–90% of nodes in the networks of Slovenian researchers (Kastrin et al., 2017). We know less about the fragmentation in patenting networks. Lissoni et al. (2013) showed that giant component sizes in patenting networks are below 30% in all science fields except two, in which they reach 60% of all nodes in the network. Their work also indicates that patenting networks including university researchers seem to be less fragmented than those also encompassing non-academic inventors, which could also indicate the effects of Mertonian norms on academic inventors. Breschi and Catalini's (2010) results indicated that patenting networks seem to have smaller giant components than co-authorship ones (no giant component in any science field encompasses more than 34% of inventors). They attribute this to the fact that when the emphasis on retaining knowledge as proprietary exists, it is also likely to limit collaboration across teams of researchers, and consequently the fragmentation of such patenting networks is "rather natural consequence" (Breschi & Catalini, 2010:20). However, the results of both Breschi and Catalini (2010) and Lissoni et al. (2013) can be influenced by the fact that they focus on particular science fields.

Next, Forti et al. (2013) could not confirm that in contrast to university researchers that only publish, those that also patent would isolate or close their networks. Both researchers that only publish and those that also patent, expand their networks in time. To the extent that working in groups is common in co-inventorship, logic dictates we should also be able to detect small worlds in patenting networks, and indeed some have been able to detect them 'clearly', e.g., Yang et al., (2021a) for transnational patent networks. However, having a small-world property was not always confirmed for patenting networks in academic settings (Balconi et al., 2004; Lissoni et al., 2013).

Lastly, previous works imply that ties that would bridge otherwise disconnected parts of the networks could be somewhat limited in patenting networks (Cassi & Plunket, 2015), with links predominantly occurring within existing components, hence making them more cliquish. Fleming et al. (2007) found a negative impact of higher cliquishness on innovation productivity, however in the university setting Beaudry et Kananian (2013) show that a higher level of cliquishness is even beneficial to a certain degree for the quality and quantity of patenting by university researchers; however, that having too much of an integrated network can then be unfavorable for patenting.

Licensing networks: between opportunistic behavior and following Mertonian norms

The macro-level social network structures emerge from the agglomeration of micro-level behavioral actions of individual actors, which result in the formation of social ties (Gulati et al., 2012; Guo et al., 2021; Prell, 2009). The network structures, including licensing networks, will thus be affected by actors' network strategies aiming to gain access to certain

resources, or actors' strategies choosing to retain some advantages derived from their activities within smaller groups.

In particular, collaborating on innovation can be seen as a collaborative cost game, actors weighting between forming (larger) networks with particular structures, to share the costs related to the activity and to increase (at least implied) benefits of collaboration (Curiel, 2013; Vivona et al., 2022); or not collaborating. The latter consequently entails forming differently structured networks, due to the perception of potential costs of collaborating outweighing its potential benefits (Connelly et al., 2014), and actors thus pursuing opportunistic behaviors (Das & Rahman, 2010; Williamson, 1985). We know that sometimes, albeit actors are able to collaborate, they are not willing to do so, i.e., exhibiting so-called ability-willingness paradox (Rondi et al., 2021).

Based on the idea of opportunistic behavior (Haeussler, 2011; Haeussler et al., 2014), the perceived feasibility of commercialization via licensing could potentially limit researchers' collaboration behavior, even more so than in patenting. Opportunistic behavior has been discussed in the literature, especially as an impediment to collaboration on organizational and interorganizational levels as well as on the individual level (Das & Rahman, 2010; Williamson, 1993). Opportunistic behavior can be divided into two forms according to stages: ex-ante and ex-post. Typically issues, such as those related to adverse selections, are considered as manifestations of ex-ante opportunistic behavior (Das & Rahman, 2010; Williamson, 1993).

Initial recognition of the potential is a prerequisite for any opportunities' recognition and related behavior, and it could trigger specific inventors' collaboration behaviors, consequently impacting network properties. O'Gorman et al. (2008) claimed that inventors initially recognize an invention's commercial potential when they are still 'embedded in their research context'. This initial recognition can stem from the inventors' 'alertness' when initially identifying their entrepreneurial opportunities during the research process (Kirzner, 1997), from their prior knowledge (Shane, 2000), or as an input from their licensing partners (Chang et al., 2009).

There are several types of opportunities arising from most commercially valuable patents, including their impact upon individuals' reputations. The potential for reputational gains can in turn reduce collaboration (Haeussler, 2011), since the perceived benefits of collaboration may not offset the potential losses incurred (Haeussler et al., 2014). These losses are in various forms, e.g., in needing to share licensing revenues, i.e., what Das and Rahman (2010) see as economic determinants of opportunistic behavior.

The decision for a more contained collaboration can also be connected to a priori considerations regarding future problems, which can impact the opportunities arising from the patent, e.g., considerations about the active involvement of a particular potential group member in collaboration with the licensee during or after the licensing process. These temporal determinants (Das & Rahman, 2010) thus include considerations related to collaboration (time) horizon. Kotha et al. (2013) researched coordination challenges in licensing and proffered evidence for such a perspective in university technology commercialization. Another significant issue is that inventors inevitably weigh the increase of the opportunities arising from collaboration with other inventors (Bozeman & Corley, 2004) as opposed to no collaboration. A negative assessment, which arises when the inventor sees no need for co-inventors' knowledge input neither in the patent nor in the licensing process; or can envision no future opportunities weighing in on the decision to collaborate and share any potential benefits arising from licensing; or the considerations connected to the ability to sanction any potential breaches (Coleman, 1988) would not outweigh the positive aspects. Such considerations can result in differences in collaboration behavior. Prior research has

indeed shown that researchers can use different collaboration strategies (Bozeman & Corley, 2004).

On the other hand, ideal Mertonian norms in science that emphasize revealing and sharing scientific resources and knowledge with colleagues (Merton, 1957) could be strong enough to counter any additional negative effects potentially caused by opportunistic behavior related to those university inventions with higher commercialization potential. Another counter-measuring effect could be consideration of the potential for future reciprocity, which can be weighed against the current diminishing of competitiveness (Haeussler et al., 2014), or connecting to individuals with previous licensing experiences (Kotha et al., 2013). Inventors rely heavily on social sources (Allen, 1977), which are especially important when there is a need to transfer tacit knowledge (Fleming et al., 2007). Such an instance may arise, for example, when dealing with patents with the highest potential, when the knowledge on the exploration (of the patented technology) is supplemented also with the tacit knowledge on exploitation (i.e., licensing), which comes beyond the licensing process itself.

Increased entrepreneurial orientation, and the considerations arising from it, can cause inventors and their groups to change their behavior; e.g., from conducting basic to conducting applied research, from focusing on publishing to focusing on patenting, and from following open science norms to adopting secrecy behavior (Shibayama et al., 2012), all of which are incompatible with traditional academic norms (Dasgupta & David, 1994). Scholars have, for example, raised concerns regarding the negative consequences of academic capitalism such as publication delay or incomplete publication (Blumenthal et al., 2006), unwillingness to share research materials (Blumenthal et al., 1997; Campbell et al., 2002; Shibayama et al., 2012; Walsh et al., 2007), and shifts toward more applied and lucrative research (Slaughter & Rhoades, 1996). Hence, commercialization potentially affects collaborative behavior, and therefore there is a need for a thorough investigation, not only of patenting, but especially of licensing networks.

In this paper, we consider whether inventors' engagement in patents with the most potential for commercialization (i.e., the licensed patents) affects the properties of their respective networks in terms of fragmentation, cliquishness, and small worlds. We investigate this first by comparing the properties of licensing networks to those of patenting networks, and next by comparing the licensing networks to randomly generated subnetworks (of the same size) of patenting networks.

Since we can construe that the interplay of opportunistic behavior versus collaboration norm pressures can be different in licensing and patenting, we first investigate whether the patenting and licensing networks at the universities exhibit similar or dissimilar fragmentation, cliquishness, and small world properties. There are several possible reasons for potential differences between collaboration in patenting and licensing networks. Both patenting and licensing are instrumental commercialization activities at universities that allow the cognitive content (i.e., the right on the invention) to be transmittable, codifiable, and protectable against the risk of appropriation (Fabiano et al., 2020). However, from a commercial value perspective, licensed inventions are often recognized as combining more distal domains, and offering more breakthrough potential, which makes them more relevant for the industry (Kotha et al., 2013). Licensed patents include the most valuable information, recognized as such by the inventors as well as acknowledged by their licensing partners. This leads to a question whether there is a specific engagement of inventors in collaboration when dealing with patents with the most potential, and whether this can be detected in the different structural properties of licensing networks compared to patenting networks. Consequently, this would point to the existence of opportunistic behavior by inventors

who license (and contrast with the predominance of Mertonian principle-led collaborative behaviors) that would result in limiting their collaborative behavior in regard to the inventions with the highest commercial potential, and consequently mirror itself in isolating and/or closing their networks.

Different sizes of networks can disallow us to directly compare different types of networks (e.g., patenting networks versus licensing networks) in order to draw definite conclusions about how fragmented or how cliquish these networks really are. As opposed to Arenius and De Clercq (2005) who explored whether and how network properties can influence the availability, timing, and quality of information access, i.e., of opportunity recognition, in this paper we also test whether we can detect that opportunity recognition can result in particularities within licensing network structures. Subsequently, we focus on licensing networks, exploring whether they exhibit some unexpected network properties diverse from those predicted by randomly created networks. To detect different collaboration behaviors of inventors in licensing networks compared to patenting networks, we perform comparisons of the licensing networks with the randomly created sample networks of the same sizes, where ties between inventors are simulated by collaborations on real patents that were not licensed.

Data and methodology

Research setting and dataset construction

Exploring the context of Japanese university commercialization has three advantages in terms of investigating licensing and patenting. First, Japanese universities' technology transfer results are rapidly increasing (Modic & Yoshioka-Kobayashi, 2020; UNITT, 2018). Second, they have relatively low levels of the so-called hidden technology transfer (Nakayama et al., 2017)—that is, university commercialization activities outside formal channels—which allowed us to capture a relatively precise picture of the situation. The third advantage is its limited policy interventions which stimulate collaborative inventing activities. The structure of patenting networks within universities is potentially affected by some innovation policy programs which enhance university-wide collaboration (e.g., center for research excellence). In this regard, Japanese research excellent programs mainly direct to basic research or educational activities, and have little attention to collaboration in technology transfer.

Despite the challenges related to the availability and accessibility of such data which have been highlighted in previous research (Bercovitz et al., 2019; Wright et al., 2014), we were able to acquire individual-level data on patenting and licensing. We used enriched patenting and licensing data based on the administrative records of two well-respected Japanese universities. Both universities exhibit strong patenting and licensing performance according to the Japanese technology transfer survey (UNITT, 2018), which ranked them among the top 10 most successful Japanese universities in terms of technology transfer. Due to confidentiality, we refer to these institutions as *University A* and *University B*.

Our database consists of patent application data and data on licensing and patent assignment between 2004 and 2014. We additionally enriched this database with data gathered from an external patent database. All patent applications include at least one inventor affiliated with one of the two universities. For every patent application, we use several

attributes: the patent's inventors, the filing date, the field of the patent, and whether or not the patent was commercialized via licensing or patent assignment (we call those 'LA patents')¹. Moreover, since we study networks of inventors, we carefully performed inventor name disambiguation (see Appendix 1) to avoid duplicated network nodes corresponding to the same individuals.

Network analysis and network properties' measures

In the next step, using the acquired data, we created networks of inventors based on their collaboration in patenting activities. The underlying structure of a network is a graph, a structure comprised of a set of nodes representing inventors and a set of ties representing some relationship between two nodes. In our case, two nodes are related if the corresponding inventors coauthored a common patent application.

We constructed two sets of networks; one set for each of the two universities. For each set of networks and for each year in the period 2004–2014, we created a network with a set of nodes comprising inventors who submitted their patent applications in the period from the first year of the analysis up to a given year. This cumulative construction enabled us to include the temporal dimension in our analysis and thus monitor how network structure evolved during the years.

Our research specifically focuses on collaboration behavior on LA patents, thus we separately analyze the networks of inventors involved exclusively in them. Specifically, we considered two types of networks with regard to the patent types:

- *patenting networks* in which the nodes represent inventors involved in some patent application, where two inventors are connected if they co-authored a common patent; and
- *licensing networks* with inventors of LA patents as the nodes, in which two nodes are connected if they co-authored a common LA patent application.

Note that the licensing networks are subnetworks of corresponding patenting networks.

We therefore consider four sets of networks; patenting networks at University A, patenting networks at University B, licensing networks at University A, and licensing networks at University B, where each of these four sets contains 11 networks, one per each period (2004–2004, ..., 2004–2014). See also Fig. 1 for a sketch of our research design diagram.

A group of inventors collaborating on a particular patent forms a clique (a subnetwork in which every node is connected to every other node); in our networks, we denote it a *patenting group*. If two patents have the same set of inventors, then they determine the same patenting group. Similar to Balconi et al. (2004), we assume that inventors belonging to the same patenting group know each other and have possibly exchanged crucial scientific or technical information. In licensing networks, inventors—beyond potentially exchanging information on issues related to exploration (scientific and technical knowledge)—are also able to share their knowledge on exploitation (sharing knowledge on licensing or selling of patents).

¹ Patent (ownership) assignments were included since they represent a typical technology transfer channel in Japan. In general, there are no one-to-one relationships either between patents and licensed patents or between patents and assigned patents. For example, a patent can neither be licensed nor assigned, or a single patent can be subject to several licenses.

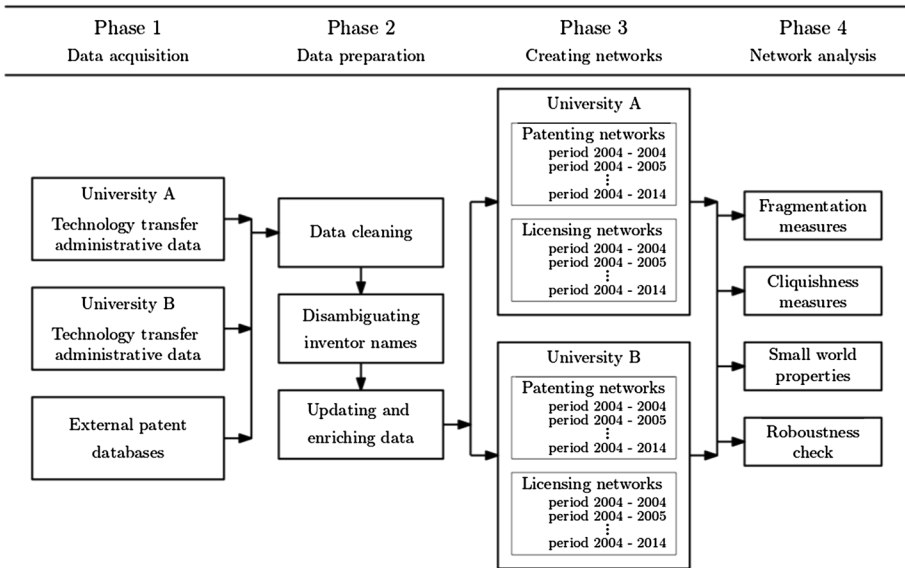


Fig. 1 A diagram of research design

Now, we describe and define network measures we are using in our analysis. We begin with two measures quantifying the degree of collaboration of individuals; namely *average degree (AVD)* and *average extended neighborhood degree*. The former being the average number of inventors’ collaborators and the latter being the average number of inventors’ collaborators together with their collaborators (i.e., the number of nodes at a distance at most two from a selected node). We usually denote the set of nodes in the neighborhood (*neighbors*) of a node X with $N(X)$, and the set of nodes at a distance at most two from X with $N_2(X)$.

Fragmentation and cliquishness of networks are not strictly defined; informally, fragmentation aims to detect how well or to which degree all network nodes are connected (i.e., global connectivity by paths), while cliquishness detects to which level the nodes in neighborhoods of individual vertices are interconnected (i.e., local connectivity of nodes with a common neighbor). Both properties can be determined using different measures in order to grasp more detailed insights, therefore we decided to use two measures per each. We also note here that the presence of one property does not imply the presence of the other; e.g., there are networks with high cliquishness and low fragmentation, or networks of any other combination of the presence of the two properties (see Fig. 2).

Fragmentation

We continue with two measures that quantify fragmentation of a network in two different ways, yet making use of the same network elements: the connected components. In network analysis, the usual substructures of networks are maximal connected subnetworks called *connected components*. A subnetwork S of a network N is *connected* if for any pair of nodes X and Y , there exists a sequence of ties such that one can traverse S , tie by tie, from X to reach Y . We say that S is *maximal* if there is no node in N , which does not belong to S , that is connected to some node in S .

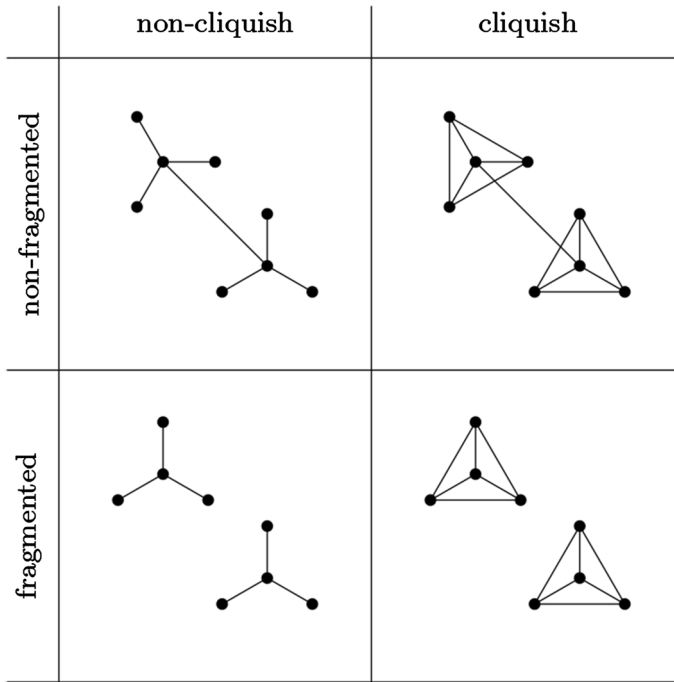


Fig. 2 A diagram of networks having four combinations of the fragmentation and cliquishness properties

A connected component in our networks represents a group of inventors who are connected through collaboration on patent applications. The largest connected component in a network N is then called the *giant component* (we denote it $GC(N)$), and it is a common phenomenon in collaboration networks (Newman, 2001). The *relative size of the giant component* of a network is the number of nodes appearing in the giant component divided with the number of all network nodes.

As the second measure of fragmentation, we use the number of all connected components in a network. This is relevant due to the fact that two networks with the same number of connected components may have very different structures (e.g., one has a huge giant component and many isolated nodes, and the other has many connected components of comparable sizes). We use the *component concentration* measure (CoC) defined in Hur and Park (2016) as.

$$CoC(N) = \sum_{C \in CC} \left(\frac{|C|}{|N|} \right)^2,$$

where N is a given network, CC is the set of connected components, $|C|$ is the number of nodes in a connected component C , and $|N|$ is the number of nodes in N .

Cliquishness

The clustering coefficient is typically used to measure cliquishness in patenting network analysis (He & Fallah, 2009; Schilling & Phelps, 2007). The *local clustering coefficient* $ClC(X)$ of a node X measures how well connected its neighbors are between each other; i.e.,

$$CIC(X) = \frac{2|E(N(X))|}{|N|(|N| - 1)}$$

where $|E(N(X))|$ denotes the number of ties between the nodes in $N(X)$. The *average local clustering coefficient* of a network N , denoted $CIC(N)$, is then computed as the average of the local clustering coefficients of all nodes. Since a high clustering coefficient for an inventor usually shows that their work is limited to research within a fixed group of coworkers, we are also interested in shares of researchers exhibiting lower values. For this reason, we also compute the relative number of inventors having local clustering coefficients equal to 1, which we denote the *local clustering index*.

Note that if an inventor X has $CIC(X) = 1$, it does not necessarily mean that they only work within one patenting group, but we assume that in the majority of instances this is the case. In order to investigate this more thoroughly, for every network in our analysis, we constructed an auxiliary two-mode network, as suggested by Newman (2001), which we call a *patenting group network*. In particular, these networks are comprised of two sets of nodes, G and I . In the former (set G), every node represents a patenting group, and in the latter (set I), every node represents an individual researcher. There are no ties between nodes within each of the two sets of nodes. Ties exist only between the two sets; hence every tie is connecting a patenting group with an inventor. Clearly, every inventor is connected to the patenting groups she/he is a member of. These networks enabled us to better understand how often inventors collaborate with different patenting groups. We computed two measures: average degree of nodes in set I , giving us an average number of patenting groups that inventors are involved with, and the relative number of nodes in set I with degree 1, i.e., being involved with only one patenting group. We call the former the *inter-group degree*, and the latter the *single-group index*.

Small worlds

To determine whether our networks exhibit small world properties, we computed their *small world coefficients*. It is well known that a precondition for a network to be a small world is that the majority of nodes are connected, i.e., having a giant component comprising at least 50% of nodes. To compute the small world coefficient of a network N , we first compute its *average path length* ($AP(N)$), i.e., the average distance between all pairs of nodes in the giant component, and then compute the *global clustering coefficient* $gCIC(N)$, defined as

$$gCIC(N) = \frac{T}{\binom{|N|}{3}}$$

where T denotes the number of triples of nodes which are pairwise connected. The *small world coefficient* ($SWC(N)$) is then computed as

$$SWC(N) = \frac{\frac{gCIC(N)}{gCIC(N_r)}}{\frac{AP(N)}{AP(N_r)}}$$

where N_r denotes a random network with the same number of nodes as the giant component $GC(N)$ in N , and its average degree being equal to the average degree in $GC(N)$, i.e., we choose a tie between every pair of nodes with the probability $AVD(GC(N)) / |GC(N)| - 1$.

Table 1 Basic network characteristics

	University A	University B
# Patent Applications	2525	3723
# Licensed Patents (a)	435	128
# Assigned Patents (b)	292	727
# LA Patents (a & b)	642	852
# Inventors	3324	5842

Robustness check

In our analysis, the sizes of patenting networks are substantially different from the sizes of licensing networks. Thus, to be able to detect differences between them, we performed a robustness check by creating a sample of 500 artificially generated networks. There are several possible ways to create sample networks (see Supplement 1 for a discussion on further alternatives to our construction of the random networks). We followed two important principles: a sample network must have a similar number of nodes as the licensing network, and it must reflect patenting collaboration behavior for non-LA patents. By the latter, we mean collaboration of inventors on non-LA patents in small groups (i.e., patenting groups), which represent cliques in the network. For a given licensing network being tested we therefore constructed sample networks by consecutively selecting a patent uniformly at random from the set of non-LA patents (from the same period for which the licensing network was constructed), then adding all the patent's inventors in the sample network as nodes (if an inventor is not already in the network), and finally adding ties between all pairs of the patent's inventors. We repeated this step until the sampled network had more nodes than the tested licensing network. Finally, we determined values of analyzed measures for each network in the sample and computed average values for every measure. In this way, we obtained expected values of measures to which we compared values of licensing networks' measures.

Results

Initial observations

In Table 1, we present the patenting and licensing data for the period 2004–2014 for both universities. In general, the universities under investigation manage to license a considerable number of their patents and are, in this respect, on par with some of the best U.S. universities. In the considered period, licensed patents accounted for 9.0% of all patents. At first glance, in comparison to some top US universities, this percentage is somewhat lower. For example, Wright et al. (2014) reported that 20% of inventions generated at the University of California in the period 1990–2005 were linked to at least one license. However, among the top eleven Japanese research universities, licensed patents accounted for 9.1% of all patents between 2013 and 2016 according to the UNITT survey. This indicates that our focal universities are both representative of the top Japanese research universities. Furthermore, in Japan, patents are commonly transferred also via assignment and therefore we

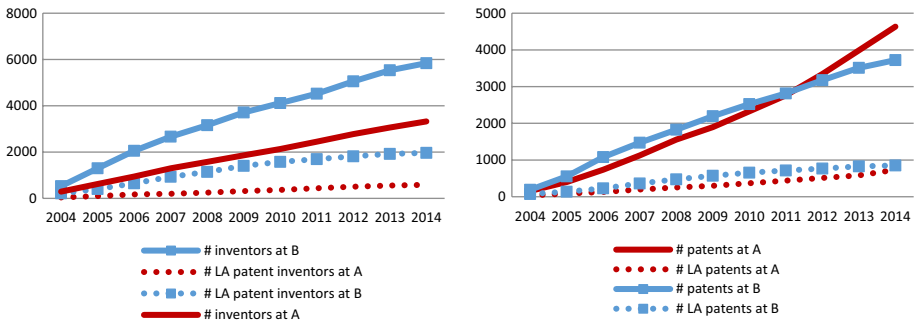


Fig. 3 Cumulative number of inventors (left) and number of patents (right)

classified them as LA patents, hence inferring that 23.9% of patents were either licensed or assigned.

We now provide some basic data to understand the general characteristics of the four sets of networks. We detected growth in the cumulative number of inventors in both sets of networks during the observed timespan at both University A and University B (see the left chart in Fig. 3). We assume this phenomenon stems from the fact that applying for patents is a common activity in entrepreneurial universities today. Regarding the LA patent inventors, their number also grew over the years although at a much slower pace, maintaining the relative rate of LA patent inventors compared to all inventors (18% at University A and 35% at University B).

In the right chart of Fig. 3, we show the cumulative number of patents and LA patents. Interestingly, the average number of inventors per patent application was almost the same at both universities. In the observed period, this average ranged from 3.15 to 4.16 at University A and from 3.86 to 4.66 at University B. When limited only to LA patents, the average ranged from 2.80 to 4.62 and from 4.04 to 4.62, respectively. These numbers are also relatively stable throughout various academic fields, with the average number being the highest for Chemistry at both universities, and with numbers remaining close to those for all other fields. Interestingly, both universities at the end of the observed period also exhibited similar average degrees (see Appendix 2) in the patenting and licensing networks, indicating that the inventors collaborated on average with around six collaborators directly (5.91 for University A and 6.42 for University B) in patenting, and on average with around five collaborators (4.88 for University A and 5.68 for University B) in licensing.

Fragmentation in patenting and licensing networks

The fragmentation of a network is often studied at the macro level through the prism of giant components. The relative sizes of giant components in the patenting networks at University A and University B grew over the observed period, comprising more than 50% and 60% of all nodes in 2014, respectively (see Fig. 4). A considerable increase can be observed at University B between 2008 and 2010, due to merging of several large connected components.

The giant components in licensing networks are smaller than in patenting networks, but even more interestingly, there is an important difference between the licensing networks in the observed two universities. At University A, the relative size of the giant component was

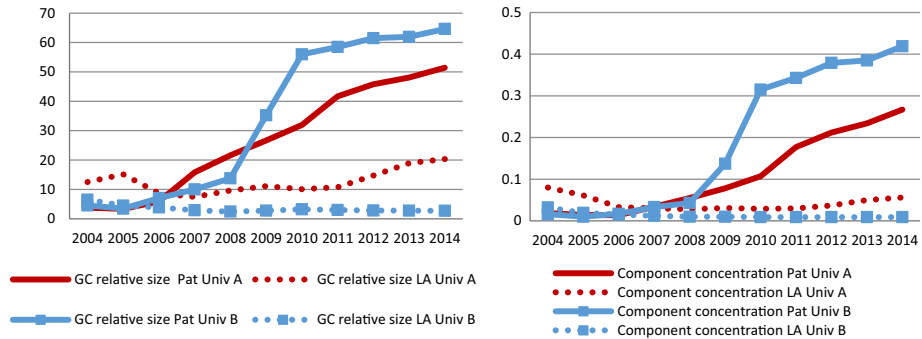


Fig. 4 Relative sizes of giant components (GC, left) and component concentrations (right)

about 20% during the observed period, which is substantially smaller than in the patenting network. However, the major difference is that at University B, a giant component did not appear at all; namely, the largest connected component in the network comprises less than 3% of nodes, i.e., inventors. At University B, this is also corroborated by a large number of connected components in the licensing network, also as compared to their number of connected components in the patent network (see Appendix 2). This indicates a fragmented network, with the nodes scattered across a relatively large number of disconnected components.

Apart from the giant component sizes, we also explored the differences in sizes of all connected components using the *component concentration* measure. Its lower value implies that inventors are more evenly distributed over connected components in the network. Contrastingly, if inventors are connected in a few large connected components within a network, then component concentration takes higher values, meaning that the fragmentation of a network is lower. The values of component concentrations in all our networks (see Appendix 2) indicate that outside the giant component, they do not contain other connected components of significant sizes. Hence, inventors outside the giant components collaborate in relatively small groups.

Cliquishness in patenting and licensing networks

We observed cliquishness through micro-level measures; namely, the *average local clustering coefficient* and *local clustering index*. We also add to the aforementioned, the measures obtained from the patenting-group network analysis: *single-group index*, allowing us to observe how many inventors belong to only one patenting group, and *inter-group degree*, stating on average how many patenting groups inventors collaborate with.

The supposition that people interact in cliquish clusters is confirmed by high values of *average local clustering coefficients* (in licensing networks spanning between 0.88 and 0.97), and the high values of the *local clustering indices* (see Table 2). The latter implies that only about one fourth of inventors connect two inventors without direct connection in the patenting networks at both universities, whereas only one fifth do so in the licensing networks. A slightly decreasing trend for both measures can be detected in all networks. However, we can observe that these measures also have higher values in licensing than in patenting networks at both universities.

Table 2 Measures of cliquishness

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Average local clustering coefficient	PAT Univ. A	0.909	0.916	0.901	0.903	0.903	0.891	0.888	0.885	0.885	0.884
	PAT Univ. B	0.94	0.926	0.901	0.896	0.894	0.893	0.889	0.888	0.888	0.888
	LA Univ. A	0.875	0.913	0.953	0.947	0.934	0.925	0.914	0.915	0.91	0.906
	LA Univ. B	0.966	0.961	0.949	0.942	0.932	0.93	0.927	0.925	0.924	0.924
Average local clustering index	PAT Univ. A	0.838	0.81	0.787	0.787	0.792	0.768	0.764	0.753	0.752	0.753
	PAT Univ. B	0.877	0.846	0.791	0.773	0.764	0.764	0.753	0.748	0.744	0.744
	LA Univ. A	0.875	0.889	0.936	0.915	0.896	0.873	0.853	0.853	0.841	0.818
	LA Univ. B	0.893	0.873	0.863	0.842	0.812	0.818	0.808	0.796	0.797	0.798
Average inter-group degree	PAT Univ. A	1.2	1.36	1.47	1.57	1.61	1.72	1.77	1.81	1.86	1.91
	PAT Univ. B	1.25	1.38	1.62	1.73	1.8	1.84	1.9	1.94	1.98	2.02
	LA Univ. A	1	1.08	1.09	1.16	1.16	1.23	1.25	1.28	1.32	1.47
	LA Univ. B	1.22	1.24	1.32	1.38	1.44	1.44	1.46	1.5	1.5	1.51
Average single-group index	PAT Univ. A	0.859	0.765	0.753	0.738	0.739	0.716	0.701	0.693	0.692	0.688
	PAT Univ. B	0.835	0.79	0.72	0.709	0.699	0.696	0.684	0.679	0.676	0.675
	LA Univ. A	1	0.919	0.913	0.841	0.855	0.841	0.839	0.842	0.831	0.8
	LA Univ. B	0.846	0.828	0.801	0.783	0.767	0.776	0.767	0.758	0.755	0.759

Analysis of patenting group networks also reveals that inventors tend to be relatively constrained in terms of working with several different groups. The average inter-group degrees are surprisingly consistent at both universities for patenting and licensing (see Table 2), with very consistent values of 1.50 at University A and 1.51 at University B for licensing in the year 2014. All values of inter-group degrees exhibit increasing trends in the observed period, yet the inventors' collaboration with more than one group remains restrained.

Additionally, cliquish behavior can be exhibited by a single-group index; a big share of inventors is only ever collaborating within their original patent groups (see Table 2). In terms of licensing networks, the numbers are surprisingly consistent. At University A, in the last observed year, 80% of inventors only collaborated within their original group in the patenting network. By comparison, 75.9% do so at University B. All trends are decreasing over the years. Furthermore, the results indicate that at both universities the licensing networks appear to be more cliquish than the patenting networks.

No small world property in licensing networks

A characteristic of most real networks are very short average path lengths, which are closely connected to the concept of the small world. In our patenting networks, the average path lengths are 6.5 and 7.5 for University A and University B, respectively (Table 3), and have an inverted U-shape, with both reaching the maximum in 2011. Furthermore, the values of small world coefficients in our patenting networks are always higher than 1 (see Table 3), implying that these networks are small worlds.

Note that in Table 3, we do not provide values for the licensing networks, since the average path length can only be computed by averaging the distances between nodes that are connected in the network. Therefore, in networks with many pairs of disjoint nodes, i.e., where the majority of nodes is not contained in one connected component, the average path length can be small, although most of the nodes are not even connected with each other. This restricts us in interpreting the values in any meaningful way. Since this is the case in our licensing networks, and the average path length is the main component in determining the small world property, we can conclude that our licensing networks are not small worlds.

Understanding licensing networks: Is all not as it seems to be?

We were particularly intrigued by the apparent differences between the giant components' sizes in licensing networks at both focal universities. The question remains if the differences between the patenting and licensing networks, and the behavior of inventors therein, reflect something more than simply differences in the sizes of these networks. In order to tackle this issue, we provide a series of random network computations and comparisons for individual measures in line with prior literature (e.g., Gay & Dousset, 2005).

The relative size of the *giant components* in licensing networks at University B are indeed smaller than expected (Fig. 5, top-right) as shown by differences between the real and expected giant components. In the years 2006–2010, there were high numbers of inventors active, but the boundary spanners that would connect the largest components in the network did not appear. On the other hand, the giant component at University A is actually larger than expected (Fig. 5, top-left). This is especially due to the strong rise in the size of the giant component in the last few years, whereas before, the GC was of a

Table 3 Measures of small world

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Average path length	PAT Univ. A 1.382	2.338	4.028	5.639	6.22	7.157	7.902	7.239	6.766	6.624	6.533
	PAT Univ. B 1.587	2.555	5.748	4.751	7.593	9.344	11.032	9.133	8.078	7.815	7.885
Small world coefficient	PAT Univ. A 1.316	3.039	3.775	11.520	22.880	24.511	42.952	78.233	96.864	91.332	123.695
	PAT Univ. B 2.609	3.159	10.337	19.041	14.948	62.623	106.170	153.565	420.506	191.106	184.672

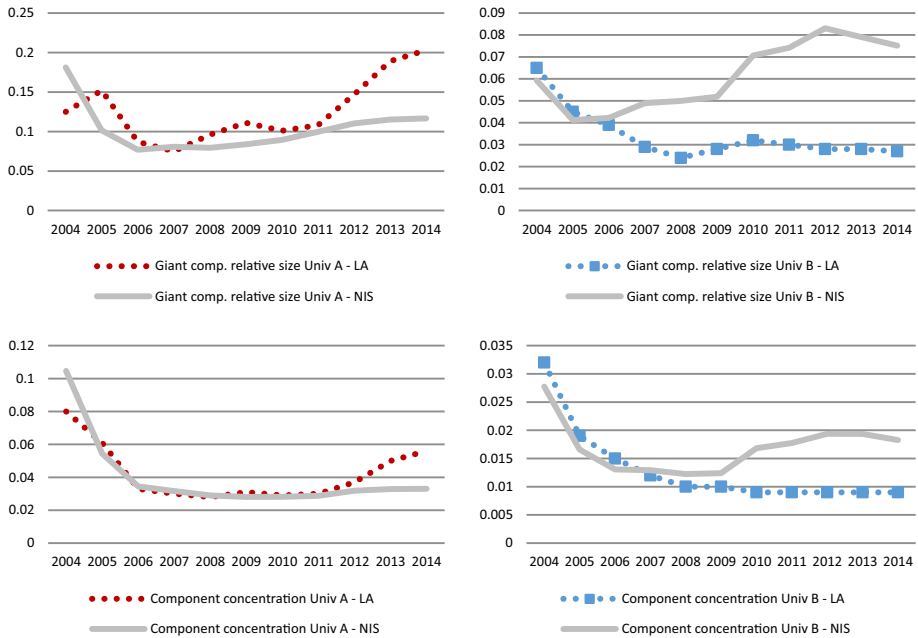


Fig. 5 Relative sizes of giant components’ sizes (row 1) and component concentrations (row 2) in licensing networks compared to the average sizes in the sample (University A, left; University B, right; LA licensing networks, NIS random networks)

relatively expected size. Interestingly, the comparisons of the component concentrations (see Fig. 5, second row) show that the licensing network at University B exhibits lower than expected *component concentration*, thus somewhat higher than expected fragmentation, which is also outside its giant components. The opposite is true for University A, where in the last period the component concentration is somewhat higher than expected.

Observing the values of the measures for cliquishness in both licensing networks allows us to discover that many of them are in ranges that would be more or less expected for such networks (see Fig. 6). Overall, both networks are slightly less cliquish than expected, but not overly so. If we focus on University A, we can observe the inventors involved in licensing cooperate with slightly more groups than expected. Meanwhile, less inventors than expected are engaged only with a single group.

At both focal universities exhibit values of cliquishness measures that are close to those predicted by our sample networks. Contrary to this, the values of fragmentation measures are distinct from those predicted by the sample networks.

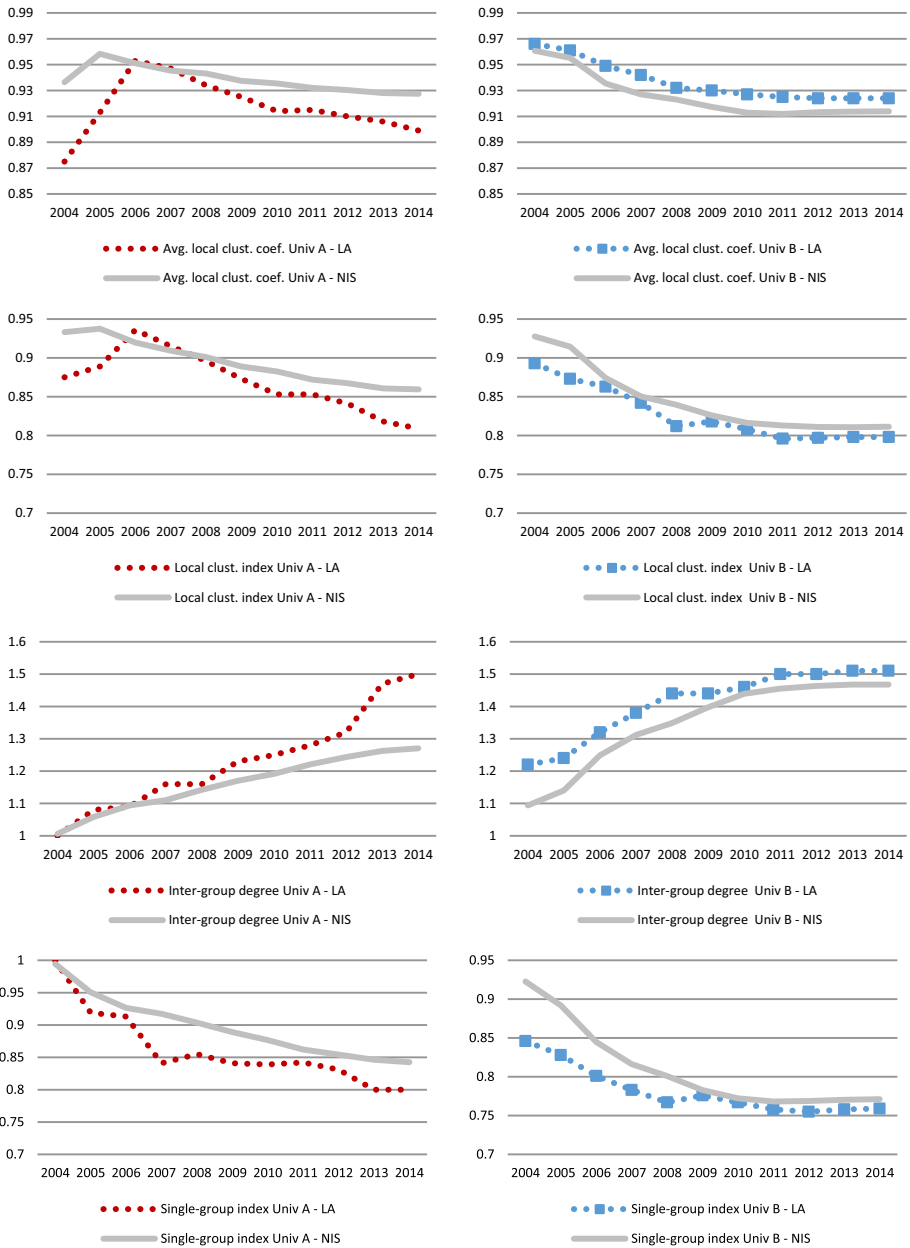


Fig. 6 Comparison of real-life licensing networks with random networks

Discussion

Discussion on patenting and licensing networks' properties

Our analysis revealed that most inventors involved in patenting activities formed large connected components in patenting networks at both focal universities and that patenting did not cause strong fragmentation. In particular, in the last year of the analysis, the relative sizes of the giant components in our patenting networks are somewhat smaller than those generally observed in the co-authorship networks; however, they still exceeded 50% of nodes at both universities. Similarly, Lissoni et al. (2013) also detected giant components in patenting networks that are, on average, above 50% (discounting for two that were extremely small).

On the other hand, in the licensing networks, fragmentation was more pronounced than in the patenting networks. The relative sizes of the giant components were about 20% at University A, but only 3% at University B. Hence, no giant component of any significant size appeared at University B, which signaled a highly fragmented licensing network. Additionally, considering the component concentration, our data shows that inventors outside the giant components collaborate in relatively small groups in licensing networks. The inventors that license are thus seemingly often parts of disjoint constellations, which may have distinct expertise, follow specific interests, and pursue their own agendas.

Social networks originating from collaboration can also exhibit contradicting network properties at the same time. A long-standing weakness of social network research was the inability to connect the micro-level interactions to macro-level network patterns in some convincing way. Even weak connectivity on the macro-level can be enough for the giant component to appear due to the existence of some boundary spanners mitigating the fragmentation. At the same time, cliquishness might still be a property of such a network.

The average values of the local clustering coefficients and indices, as well as the values of inter-group degrees and single-group indices evince that both patenting and licensing networks of both universities are very cliquish. Furthermore, while neither the patenting, nor the licensing networks are of the same size in the last observed year, the values are surprisingly consistent. As seen from the local clustering index values in all networks, only a few inventors (1/4 of inventors in patenting and 1/5 in licensing networks) connect pairs of their neighbors which were not directly connected. This suggests that most of the ties are redundant, or *mutatis mutandis*, signaling that mostly these ties reinforce existing collaborations. We can detect a slightly decreasing trend in the values of the clustering index if taking into account the whole period values, meaning that over time there are somewhat more people who act as boundary spanners between previously unconnected individuals.

Furthermore, while all values of inter-group degrees exhibit increasing trends in the observed period at both universities, the inventors still collaborate in patenting networks on average with only two groups, and even less in licensing, on average solely with one and a half groups. This also reinforces our previous assumption that many groups most likely work independently of each other. Lastly, the single-group index reveals very consistent patterns for both pairs of patenting and licensing networks. These two measures therefore also confirm that, over time, networks are becoming less cliquish.

As expected, we confirm that patenting networks at both universities are small worlds in line with the evidence of research on patenting networks typically done outside the university settings (Guan & Shi, 2012; Hung & Wang, 2010). On the other hand, licensing networks are not small worlds. We specifically note that lacking the small-world property

can be contingent on other network properties, such as a high level of fragmentation, which disallows the formation of a small world. Our conclusions are seemingly opposing the findings of Yang et al. (2021b), which claim to detect the small worlds, but they do so while focusing on the inter-regional level. However, the interpersonal networks we explore, are highly fragmented, and consequently, are lacking the benefits of small worlds, i.e., short path lengths allowing the inventors to be exposed to non-local perspectives and apt to ensure fast and widespread diffusion of knowledge (Fleming et al., 2007; Uzzi & Spiro, 2005).

Licensing networks: do recognized opportunities make them different than expected?

We address the concerns that researchers are more conservative when starting a collaboration when dealing with university inventions with recognized higher commercialization potential. Several results, especially those related to a distinct lack of a giant component in the licensing networks at University B, have at first glance signaled distinct collaboration patterns for inventors who collaborate on patents that were licensed. Furthermore, it is possible to infer that different types of networks of inventors that are involved in various types of knowledge transfer activities, could exhibit different structural properties; e.g., the giant components in publication networks appear to be significantly larger than those in patenting (see, e.g., Breschi & Catalini, 2010). This indicates that there can be a negative incentive for collaboration in academic entrepreneurship to maintain secrecy and exclusiveness following an opportunity-based collaboration behavior. However, in the networks that encompass more than one activity by the same inventors, there is typically also a difference in the sizes of these networks themselves. In particular, in our analysis, based on the fact that licensing networks are subnetworks of patenting networks, we compared the licensing networks with randomly chosen subnetworks of patenting networks of the same sizes, confirming that licensing networks indeed have essentially smaller giant components than patenting networks.

Although we did observe that the relative size of the giant component of the licensing network at University B was two and a half times lower than expected, we did, on the contrary, discover that the giant component of the licensing network at University A was in fact bigger than expected. Similarly, the component concentrations' values indicated a less fragmented network than expected at University B, also outside the giant component, and a more fragmented network than expected at University A. This implies that there are contextual reasons influencing the fragmentation of licensing networks at universities. Similarly, opportunity recognition in terms of the commercialization potential for licensing does not seem to imply more cliquish behavior per se, as implied by our results for University A. For example, there is a specific university-wide research program, a globally recognized center of excellence in applied research at University A which could explain that. Such types of institutional settings seem to affect inventor's within-university collaborative behavior. Thus, we were unable to find evidence to support the notion that (initial) opportunity recognition would automatically lead to more restrained behavior.

At this point, one may wonder how the LA patent inventors collaborated when dealing with non-LA patents. For this purpose, we analyzed networks of LA patent inventors with additional ties added; namely, we extended the licensing networks by connecting two inventors also if they co-invented a non-LA patent. With this approach, at University A, the relative size of the giant component increased from 20 to 30% in 2014. While this is already a considerable increase, at University B, the difference was even more pronounced. The relative size of

the giant component was 55% (in contrast with the 3% observed in their licensing network) in 2014. We therefore observed that when dealing with patents with high (commercialization) potential, i.e., licensed patents, these inventors are more ‘monogamous’ (Bercovitz & Feldman, 2010), but less so when engaged in patenting activity in general, causing also a reconfiguration in the respective networks. In other words, inventors involved in licensing activities exhibit what we can call a dualistic opportunistic behavior, since their collaboration is substantially less limited when involved in patenting activities in general. However, the simplified idea of opportunistic behavior does not perfectly explain this finding. If the inventors are actually opportunistic, they would prefer to join a giant network, in which they might find another opportunity to commercialize by collaborating with other teams.

Conclusion

We explored networks of inventors at two universities in order to gain insight into the properties of the patenting and licensing networks and the differences between them. Both focal universities exhibited strong patenting and licensing activity providing a rich research setting. Focusing on several different properties of network structures conjointly, i.e., fragmentation, cliquishness, and small worlds, allowed us also to reconcile potentially contrasting implications. In addition, having data spanning more than a decade allowed us to understand how these properties are evolving over time. In order to provide robust evidence of our claims on detected network properties, we introduced additional measures for both the fragmentation and the cliquishness; e.g., for fragmentation we also introduced a measure to provide an insight into fragmentation outside the giant component; to better understand cliquishness, we went beyond the most typically used clustering coefficients and constructed three measures, which are based on a construction of an auxiliary two-mode network, as suggested by Newman (2001).

Clarifying the implications of cliquish and fragmented network structures for various organizational outcomes is important to our understanding of network resources. We reveal that, in contrast to licensing networks, patenting networks are not especially fragmented. However, the trends in the values of the two measures we use for fragmentation are quite distinct, which is due to the connecting of larger components at the university where we detect an abrupt rise. Fleming et al. (2007) report on their attempt to understand more by identifying and interviewing the inventors who allowed the linking of components into the giant component along with similar ‘counterfactual’ non-linking inventors.

Not finding small worlds in licensing networks is somewhat interesting, since there is little evidence in existing literature about social networks not being small worlds. In terms of inventors and their groups, when licensing, they remain relatively isolated. Hence, the sharing of knowledge gained by licensing to different licensees and the related further collaboration with the licensees (needed due to university inventions for the large part being embryonic), does not necessarily occur naturally through the collaboration of different groups that license. Instead, planned efforts to allow them to connect could provide such benefits.

We contribute to the debates on the effects of increased commercialization efforts on a network structure at universities in terms of inventors involved in licensing. We also combined the opportunity recognition and opportunistic behavior literature with the stream of literature dealing with collaboration benefits and strategies, and the Mertonian norms of sharing, to examine whether potential opportunity recognition would drive licensing networks to be more fragmented and more cliquish as expected. Based on our robustness check,

in terms of cliquishness, we found that they are about as cliquish as expected. However, in terms of fragmentation, we found evidence of both more fragmented networks as well as less fragmented networks than expected, which indicates that there are other factors at play.

This concurs with the assessments that the collaboration behavior of inventors, when dealing with the most commercialization potential, i.e., licensed patents, is most likely affected by institutional characteristics such as incentives, norms and geographical proximity (Bozeman & Corley, 2004), or other contextual factors. Hence, although our findings may have some limitations in regard to generalizability due to the different contextual settings, these limitations are key stepping-stones in understanding university commercialization and collaboration mechanisms in other university settings. Our results do not allow us to conclude that increased commercialization opportunities cause more fragmentation, and hence this does not follow the logic of debates on changed behaviors as a consequence. There could be several reasons why we cannot detect this, e.g., a) there might not be an initial recognition of this potential; b) the general Mertonian norms of sharing and collaboration might be so prevailing that they neutralize any effects to the contrary; c) opportunity-based behavior arising from commercialization potential does not overshadow the well-recorded assessments of collaboration benefits (see, e.g., Bozeman & Corley, 2004).

Whilst more research is needed, the latter of the aforementioned reasons might be the most suitable interpretation of our results. But we do find evidence of what we call the dualistic behavior of inventors. Even when inventors' licensing networks are highly fragmented, their patenting networks are not. When collaborating on non-licensed patents, inventors extend their collaborations to new collaborators, and they do not simply strengthen ties with existing collaborators. This would indicate that there are some diverse strategies used when engaging with patents having the most commercial potential or at least that in some cases inventors are able to recognize this potential. Furthermore, inventors' dualistic opportunistic behavior may also be exacerbated when they take potential requests from licensees into account (Brouwer, 2005), particularly to limit their collaboration. Again, more research is needed to determine how much licensees influence the behavior of inventors.

Our findings suggest that a limited number of inventors commit to inter-group collaboration, while the majority of inventors maintain single-group collaboration. Policy makers and top management teams at universities often emphasize both inter-group collaborations and commercialization of academic achievements, and sometimes provide research grants or internal incentives for interdisciplinary and translational collaborative research. Our findings urge caution in the implementation of these incentive mechanisms. Motivating researchers to enter new collaborations can be contradictory for those who have already committed to commercially feasible research. These incentives might also contradict their opportunity recognition assessments.

Prior research has generally investigated technology transfer, university patenting, and university licensing using US, European, or more recently, Chinese data. However, improving technology transfer results and strong formal technology transfer pathways—namely, patenting and licensing—makes Japan a premier environment to study university commercialization efforts. In general, we need to understand more about technology systems in their earlier stages, since evidence-based policy directions and managerial recommendations are crucial to steer them towards maturity.

Appendix 1: name disambiguation process

Our *name disambiguation process* included several steps: 1) as some Japanese characters have multiple styles, we first determined names including these characters and detected same names; 2) next, we checked through all names and picked up misspellings or mistakes in the order of surname and first name; 3) names given only in Latin characters were carefully matched with Japanese names when they appeared to be typical Japanese names; 4) to double check, we have used the combination of name and no-name variables for inventors (this being the field of the technology and the inventor network). We manually examined the remaining ambiguous cases (re-checking affiliation titles, checking information in the university researcher directory and the national researcher information portal, Researchmap, and checking for common licensees, common joint applicants, and the proximity of the technologies' titles).

Appendix 2: overview of network measures

		2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Basic characteristics												
Number of Nodes	PAT Univ. A	291	620	945	1300	1575	1863	2134	2451	2780	3060	3324
	PAT Univ. B	528	1298	2055	2669	3163	3712	4117	4524	5054	5533	5842
	LA Univ. A	40	99	173	201	249	315	367	436	503	555	585
	LA Univ. B	214	402	648	934	1146	1405	1576	1695	1815	1922	1964
Number of Patents	PAT Univ. A	159	401	736	1126	1558	1895	2328	2761	3342	3988	4634
	PAT Univ. B	190	553	1079	1472	1826	2193	2522	2814	3174	3511	3723
	LA Univ. A	35	84	132	197	254	300	368	437	512	581	735
	LA Univ. B	76	136	230	362	473	572	657	717	769	827	852
Average degree	PAT Univ. A	3.76	4.6	4.64	4.8	4.9	5.42	5.54	5.64	5.75	5.87	5.91
	PAT Univ. B	4.75	5.04	5.31	5.76	5.84	5.94	6.06	6.21	6.32	6.39	6.42
	LA Univ. A	2.2	4	3.7	3.83	3.81	4.27	4.29	4.38	4.41	4.92	4.88
	LA Univ. B	5.02	5.07	5.23	5.37	5.42	5.47	5.52	5.7	5.66	5.7	5.68

		2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Average extended neighborhood degree	PAT Univ. A	4.42	7.08	9.24	12.26	14.38	17.74	20.52	24.81	28.87	35.09	37.7
	PAT Univ. B	7.32	9.63	14.52	19.51	21.62	23.75	26.84	29.12	31.91	34.08	35.37
	LA Univ. A	2.2	4.53	4.43	4.68	5.11	6.67	7.32	10.27	13.58	24.1	28.38
	LA Univ. B	5.78	6.72	8.6	9.52	10.06	10.82	11.3	12	12.21	12.89	13.2
Fragmentation												
Relative size of giant component	PAT Univ. A	0.038	0.034	0.059	0.158	0.216	0.267	0.32	0.417	0.458	0.481	0.514
	PAT Univ. B	0.045	0.035	0.071	0.1	0.138	0.352	0.56	0.585	0.615	0.619	0.646
	LA Univ. A	0.125	0.152	0.087	0.075	0.096	0.111	0.101	0.108	0.147	0.189	0.203
	LA Univ. B	0.065	0.045	0.039	0.029	0.024	0.028	0.032	0.03	0.028	0.028	0.027
Component concentration	PAT Univ. A	0.019	0.014	0.014	0.034	0.055	0.078	0.107	0.177	0.212	0.234	0.267
	PAT Univ. B	0.016	0.01	0.017	0.033	0.043	0.137	0.315	0.343	0.379	0.385	0.419
	LA Univ. A	0.08	0.061	0.033	0.03	0.028	0.031	0.029	0.03	0.037	0.05	0.056
	LA Univ. B	0.032	0.019	0.015	0.012	0.01	0.01	0.009	0.009	0.009	0.009	0.009
Cliquishness												
Average local clustering coefficient	PAT Univ. A	0.909	0.916	0.901	0.903	0.903	0.891	0.888	0.885	0.885	0.885	0.884
	PAT Univ. B	0.94	0.926	0.901	0.896	0.894	0.893	0.889	0.888	0.888	0.888	0.888
	LA Univ. A	0.875	0.913	0.953	0.947	0.934	0.925	0.914	0.915	0.91	0.906	0.899
	LA Univ. B	0.966	0.961	0.949	0.942	0.932	0.93	0.927	0.925	0.924	0.924	0.924
Average local clustering index	PAT Univ. A	0.838	0.81	0.787	0.787	0.792	0.768	0.764	0.753	0.753	0.752	0.753
	PAT Univ. B	0.877	0.846	0.791	0.773	0.764	0.764	0.753	0.748	0.744	0.744	0.744
	LA Univ. A	0.875	0.889	0.936	0.915	0.896	0.873	0.853	0.853	0.841	0.818	0.809
	LA Univ. B	0.893	0.873	0.863	0.842	0.812	0.818	0.808	0.796	0.797	0.798	0.798

		2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Average inter-group degree	PAT Univ. A	1.2	1.36	1.47	1.57	1.61	1.72	1.77	1.81	1.86	1.91	1.95
	PAT Univ. B	1.25	1.38	1.62	1.73	1.8	1.84	1.9	1.94	1.98	2	2.02
	LA Univ. A	1	1.08	1.09	1.16	1.16	1.23	1.25	1.28	1.32	1.47	1.5
	LA Univ. B	1.22	1.24	1.32	1.38	1.44	1.44	1.46	1.5	1.5	1.51	1.51
Average single-group index	PAT Univ. A	0.859	0.765	0.753	0.738	0.739	0.716	0.701	0.693	0.692	0.69	0.688
	PAT Univ. B	0.835	0.79	0.72	0.709	0.699	0.696	0.684	0.679	0.676	0.677	0.675
	LA Univ. A	1	0.919	0.913	0.841	0.855	0.841	0.839	0.842	0.831	0.8	0.8
	LA Univ. B	0.846	0.828	0.801	0.783	0.767	0.776	0.767	0.758	0.755	0.758	0.759

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s11192-022-04564-7>.

Acknowledgements We thank the anonymous reviewers and the editor who gave us constructive feedback to improve the paper. We are also grateful to Professor James Cunningham for providing us with helpful comments for our paper development.

Funding Open access funding provided by Nord University. This work was partly supported by the JSPS International Research Grant ID No. 16774 (D. Modic), the Slovenian Research Agency Program P1–0383 (B. Lužar), and by JSPS KAKENHI Grant Numbers JP16K03907 and JP19H01692 (T. Yoshioka-Kobayashi).

Declarations

Conflict of interest We have no conflict of interest as well as no competing interests to disclose.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly*, 45(3), 425–455.
- Allen, T. J. (1977). *Managing the Flow of Technology: Technology Transfer and the Dissemination of Technological Information Within the R&D Organization*. MIT Press.
- Arenius, P., & De Clercq, D. (2005). A network-based approach on opportunity recognition. *Small Business Economics*, 24(3), 249–265.

- Badar, K., Hite, J. M., & Badir, Y. F. (2013). Examining the relationship of co-authorship network centrality and gender on academic research performance: The case of chemistry researchers in Pakistan. *Scientometrics*, 94(2), 755–775.
- Balconi, M., Breschi, S., & Lissoni, F. (2004). Networks of inventors and the role of academia: An exploration of Italian patent data. *Research Policy*, 33(1), 127–145.
- Beaudry, C., & Kananian, R. (2013). Follow the (industry) money—the impact of science networks and industry-to-university contracts on academic patenting in nanotechnology and biotechnology. *Industry and Innovation*, 20(3), 241–260.
- Bercovitz, J., Changoluisa, J., Feldman, M. P., & Modic, D. (2019). Pay to Play: Connecting university research funding to licensing outcomes. In F. J. Contractor & J. J. Reuer (Eds.), *Frontiers of Strategic Alliance Research: Negotiating, Structuring and Governing Partnerships* (pp. 457–471). Cambridge University Press.
- Bercovitz, J., & Feldman, M. P. (2006). Entrepreneurial universities and technology transfer: A conceptual framework for understanding knowledge-based economic development. *The Journal of Technology Transfer*, 31(1), 175–188.
- Bercovitz, J., & Feldman, M. P. (2010). The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. *Research Policy*, 40(1), 81–93.
- Berghaeuser, H., & Hoelscher, M. (2020). Reinventing the Third Mission of Higher Education in Germany: Political frameworks and universities' reactions. *Tertiary Education and Management*, 26, 57–76.
- Blumenthal, D., Campbell, E. G., Anderson, M. S., Causino, N., & Louis, K. S. (1997). Withholding research results in academic life science: Evidence from a national survey of faculty. *JAMA*, 277(15), 1224–1228.
- Blumenthal, D., Campbell, E., Gokhale, M., Yucel, R., Clarridge, B., Hilgartner, S., & Holtzman, N. (2006). Data withholding in genetics and the other life sciences: Prevalences and predictors. *Academic Medicine*, 81, 137–145.
- Boschma, R., & Frenken, K. (2009). The spatial evolution of innovation networks: A proximity perspective. In R. Boschma & R. Martin (Eds.), *Handbook of Evolutionary Economic Geography*. Edward Elgar.
- Bozeman, B., & Corley, E. (2004). Scientists' collaboration strategies: Implications for scientific and technical human capital. *Research Policy*, 33(4), 599–616.
- Breschi, S., & Catalini, C. (2010). Tracing the links between science and technology: An exploratory analysis of scientists' and inventors' networks. *Research Policy*, 39(1), 14–26.
- Brouwer, M. (2005). Entrepreneurship and university licensing. *The Journal of Technology Transfer*, 30(3), 263–270.
- Brown, J. S., & Duguid, P. (2001). Knowledge and organization: A social-practice perspective. *Organization Science*, 12(2), 198–213.
- Burt, R. S. (2005). *Brokerage and closure: An introduction to social capital*. Oxford University Press.
- Campbell, E. G., Clarridge, B. R., Gokhale, M., Birenbaum, L., Hilgartner, S., Holtzman, N. A., & Blumenthal, D. (2002). Data withholding in academic genetics: Evidence from a national survey. *JAMA*, 287(4), 473–480.
- Casper, S. (2013). The spill-over theory reversed: The impact of regional economies on the commercialization of university science. *Research Policy*, 42(8), 1313–1324.
- Cassi, L., & Plunket, A. (2015). Research collaboration in co-inventor networks: Combining closure, bridging and proximities. *Regional Studies*, 49(6), 936–954.
- Cattani, G., & Rotolo, D. (2014). An exploratory study of the role of publishing inventors in nanotechnology', understanding the relationship between networks and technology, creativity and innovation. *Technology, Innovation, Entrepreneurship and Competitive Strategy*, 13, 97–122.
- Cesaroni, F., & Piccaluga, A. (2016). The activities of university knowledge transfer offices: Towards the third mission in Italy. *The Journal of Technology Transfer*, 41(4), 753–777.
- Chang, Y. C., Yang, P. Y., & Chen, M. H. (2009). The determinants of academic research commercial performance: Towards an organizational ambidexterity perspective. *Research Policy*, 38(6), 936–946.
- Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94, 95–120.
- Connelly, D. R., Zhang, J., & Faerman, S. (2014). The paradoxical nature of collaboration. *Big Ideas in Collaborative Public Management* (pp. 27–45). Routledge.
- Crescenzi, R., Filippetti, A., & Iammarino, S. (2017). Academic inventors: Collaboration and proximity with industry. *The Journal of Technology Transfer*, 42(4), 730–762.
- Crescenzi, R., Nathan, M., & Rodríguez-Pose, A. (2016). Do inventors talk to strangers? On proximity and collaborative knowledge creation. *Research Policy*, 45(1), 177–194.
- Cunningham, J. A., & O'Reilly, P. (2018). Macro, meso and micro perspectives of technology transfer. *The Journal of Technology Transfer*, 43(3), 545–557.

- Curiel, I. (2013). *Cooperative Game Theory and Applications: Cooperative Games Arising from Combinatorial Optimization Problems*. Springer.
- Das, T. K., & Rahman, N. (2010). Determinants of partner opportunism in strategic alliances: A conceptual framework. *Journal of Business and Psychology*, 25(1), 55–74.
- Dasgupta, P., & David, P. A. (1994). Toward a new economics of science. *Research Policy*, 23(5), 487–521.
- De Prato, G., & Nepelski, D. (2014). Global technological collaboration network: Network analysis of international co-inventions. *The Journal of Technology Transfer*, 39(3), 358–375.
- Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From National Systems and “Mode 2” to a Triple Helix of university–industry–government relations. *Research Policy*, 29(2), 109–123.
- Fabiano, G., Marcellusi, A., & Favato, G. (2020). Channels and processes of knowledge transfer: How does knowledge move between university and industry? *Science and Public Policy*, 47(2), 256–270.
- Fleming, L., King, C., III., & Jud, A. I. (2007). Small worlds and regional innovation. *Organization Science*, 18(6), 938–954.
- Fleming, L., & Marx, M. (2006). Managing creativity in small worlds. *California Management Review*, 48(4), 6–27.
- Forti, E., Franzoni, C., & Sobrero, M. (2013). Bridges or isolates? Investigating the social networks of academic inventors. *Research Policy*, 42(8), 1378–1388.
- Gay, B., & Dousset, B. (2005). Innovation and network structural dynamics: Study of the alliance network of a major sector of the biotechnology industry. *Research Policy*, 34(10), 1457–1475.
- Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology*, 78, 1360–1380.
- Guan, J., & Liu, N. (2016). Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. *Research Policy*, 45(1), 97–112.
- Guan, J., & Shi, Y. (2012). Transnational citation, technological diversity and small world in global nanotechnology patenting. *Scientometrics*, 93(3), 609–633.
- Gulati, R., Sytch, M., & Tatarynowicz, A. (2012). The rise and fall of small worlds: Exploring the dynamics of social structure. *Organization Science*, 23(2), 449–471.
- Guo, M., Yang, N., Wang, J., Zhang, Y., & Wang, Y. (2021). How do structural holes promote network expansion? *Technological Forecasting and Social Change*, 173, 121129.
- Haeussler, C. (2011). Information-sharing in academia and the industry: A comparative study. *Research Policy*, 40(1), 105–122.
- Haeussler, C., Jiang, L., Thursby, J., & Thursby, M. (2014). Specific and general information sharing among competing academic researchers. *Research Policy*, 43(3), 465–475.
- He, J., & Fallah, M. H. (2009). Is inventor network structure a predictor of cluster evolution? *Technological Forecasting and Social Change*, 76(1), 91–106.
- Hong, W., & Walsh, J. P. (2009). For money or glory? Commercialization, competition, and secrecy in the entrepreneurial university. *The Sociological Quarterly*, 50(1), 45–171.
- Hu, T., & Zhang, Y. (2021). A spatial–temporal network analysis of patent transfers from US universities to firms. *Scientometrics*, 126, 27–54.
- Huggins, R., Prokop, D., & Thompson, P. (2020). Universities and open innovation: The determinants of network centrality. *The Journal of Technology Transfer*, 45(3), 718–757.
- Hung, S. W., & Wang, A. P. (2010). Examining the small world phenomenon in the patent citation network: A case study of the radio frequency identification (RFID) network. *Scientometrics*, 82(1), 121–134.
- Hur, W., & Park, J. (2016). Network patterns of inventor collaboration and their effects on innovation outputs. *Sustainability*, 8(4), 295.
- Kastrin, A., Klisara, J., Lužar, B., & Povh, J. (2017). Analysis of Slovenian research community through bibliographic networks. *Scientometrics*, 110(2), 791–813.
- Kirzner, I. (1997). Entrepreneurial discovery and the competitive market process: An Austrian approach. *Journal of Economic Literature*, 35, 60–85.
- Kotha, R., George, G., & Srikanth, K. (2013). Bridging the mutual knowledge gap: Coordination and the commercialization of university science. *Academy of Management Journal*, 56(2), 498–524.
- Landry, R., & Amara, N. (1998). The impact of transaction costs on the institutional structuration of collaborative academic research. *Research Policy*, 27(9), 901–913.
- Lin, N. (2001). *Social capital: A theory of social structure and action*. Cambridge University Press.
- Lissoni, F., Llerena, P., & Sanditov, B. (2013). Small worlds in networks of inventors and the role of academics: An analysis of France. *Industry and Innovation*, 20(3), 195–220.
- Merton, R. K. (1957). Priorities in scientific discovery: A chapter in the sociology of science. *American Sociological Review*, 22(6), 635–659.
- Modic, D., & Yoshioka-Kobayashi, T. (2020). Individual-level determinants of academic patent licensing to start-ups: Impacts of principal investigators’ embeddedness in the industry. In A. Novotny,

- E. Rasmussen, T. H. Clausen, & J. Wiklund (Eds.), *Research Handbook on Start-Up Incubation Ecosystems*. Cheltenham: Edward Elgar Publishing.
- Morescalchi, A., Pammolli, F., Penner, O., Petersen, A. M., & Riccaboni, M. (2015). The evolution of networks of innovators within and across borders: Evidence from patent data. *Research Policy*, *44*(3), 651–668.
- Nakayama, Y., Hosono, M., & Tomizawa, H. (2017). *Comprehensive Survey on Patent Applications Based on Inventions by National University Researchers*. NISTEP. Available at: <http://www.nistep.go.jp/archives/35126>.
- Nelson, R. R. (2004). The market economy, and the scientific commons. *Research Policy*, *33*(3), 455–471.
- Newman, M. E. (2001). Scientific collaboration networks. I. Network construction and fundamental results. *Physical Review E*, *64*(1), 016131.
- Newman, M. E., & Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, *69*(2), 026113.
- Newman, M. E., Strogatz, S., & Watts, D. (2001). Random graphs with arbitrary degree distributions and their applications. *Physical Review E*, *64*, 026118.
- O’Gorman, C., Byrne, O., & Pandya, D. (2008). How scientists commercialise new knowledge via entrepreneurship. *The Journal of Technology Transfer*, *33*(1), 23–43.
- Panetti, E., Parmentola, A., Ferretti, M., & Reynolds, E. B. (2020). Exploring the relational dimension in a smart innovation ecosystem: A comprehensive framework to define the network structure and the network portfolio. *The Journal of Technology Transfer*, *45*(6), 1775–1796.
- Perry-Smith, J. E., & Shalley, C. E. (2003). The social side of creativity: A static and dynamic social network perspective. *Academy of Management Review*, *28*(1), 89–106.
- Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of Management*, *38*(4), 1115–1166.
- Prell, C. (2009). Linking social capital to small-worlds: A look at local and network-level processes and structure. *Methodological Innovations Online*, *4*(1), 8–22.
- Prell, C. (2012). *Social network analysis: History, theory and methodology*. Sage.
- Rondi, E., De Massis, A., & Kraus, S. (2021). Servitization through open service innovation in family firms: Exploring the ability-willingness paradox. *Journal of Business Research*, *135*, 436–444.
- Schilling, M. A., & Phelps, C. C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science*, *53*(7), 1113–1126.
- Shane, S. (2000). Prior knowledge and the discovery of entrepreneurial opportunities. *Organization Science*, *11*(4), 448–469.
- Shibayama, S. (2015). Academic commercialization and changing nature of academic cooperation. *Journal of Evolutionary Economics*, *25*(2), 513–532.
- Shibayama, S., Walsh, J. P., & Baba, Y. (2012). Academic entrepreneurship and exchange of scientific resources: Material transfer in life and materials sciences in Japanese universities. *American Sociological Review*, *77*(5), 804–830.
- Slaughter, S., & Rhoades, G. (1996). The emergence of a competitiveness research and development policy coalition and the commercialization of academic science and technology. *Science, Technology, & Human Values*, *21*(3), 303–339.
- Spithoven, A., Vlegels, J., & Ysebaert, W. (2019). Commercializing academic research: A social network approach exploring the role of regions and distance. *The Journal of Technology Transfer*. <https://doi.org/10.1007/s10961-019-09740-1>
- Subramanian, A. M., Limb, K., & Sok, P.-H. (2013). When birds of a feather don’t flock together: Different scientists and the roles they play in biotech R&D alliances. *Research Policy*, *42*(3), 595–612.
- Tahmooresnejad, L., & Beaudry, C. (2018). The importance of collaborative networks in Canadian scientific research. *Industry and Innovation*, *25*(10), 990–1029.
- Tu, J. (2019). What connections lead to good scientific performance? *Scientometrics*, *118*(2), 587–604.
- UNITT. (2018). *UNITT University Technology Transfer Survey FY2017*. UNITT.
- Uzzi, B., & Spiro, J. (2005). Collaboration and creativity: The small world problem. *American Journal of Sociology*, *111*(2), 447–504.
- Velden, T., Haque, A. U., & Lagoze, C. (2010). A new approach to analyzing patterns of collaboration in co-authorship networks: Mesoscopic analysis and interpretation. *Scientometrics*, *85*(1), 219–242.
- Vivona, R., Demircioglu, M. A., & Audretsch, D. B. (2022). The cost of collaborative innovation. *The Journal of Technology Transfer*. <https://doi.org/10.1007/s10961-022-09933-1>
- von Proff, S., & Brenner, T. (2014). The dynamics of inter-regional collaboration: An analysis of co-patenting. *The Annals of Regional Science*, *52*(1), 41–64.

- Walsh, J. P., Cohen, W. M., & Cho, C. (2007). Where excludability matters: Material versus intellectual property in academic biomedical research. *Research Policy*, *36*(8), 1184–1203.
- Wang, J. (2016). Knowledge creation in collaboration networks: Effects of tie configuration. *Research Policy*, *45*(1), 68–80.
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’ networks. *Nature*, *393*(6684), 440–442.
- Williamson, O. E. (1985). *The Economic Institutions of Capitalism*. Free Press.
- Williamson, O. E. (1993). Opportunism and its critics. *Managerial and Decision Economics*, *14*(2), 97–107.
- Wright, B., Drivas, K., Lei, Z., & Merrill, S. (2014). Technology transfer: Industry-funded academic inventions boost innovation. *Nature*, *507*, 297–299.
- Wu, Y., Welch, E. W., & Huang, W. L. (2015). Commercialization of university inventions: Individual and institutional factors affecting licensing of university patents. *Technovation*, *36–37*, 12–25.
- Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, *316*(5827), 1036–1039.
- Yang, W., Yu, X., Wang, D., Yang, J., & Zhang, B. (2021b). Spatio-temporal evolution of technology flows in China: Patent licensing networks 2000–2017. *The Journal of Technology Transfer*, *46*, 1674–1703.
- Yang, W., Yu, X., Zhang, B., & Huang, Z. (2021a). Mapping the landscape of international technology diffusion (1994–2017): Network analysis of transnational patents. *The Journal of Technology Transfer*, *46*, 138–171.
- Yayavaram, S., & Ahuja, G. (2008). Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. *Administrative Science Quarterly*, *53*(2), 333–362.
- Ye, Y., De Moortel, K., & Crispeels, T. (2020). Network dynamics of Chinese university knowledge transfer. *The Journal of Technology Transfer*, *45*, 1228–1254.
- Zhao, Z., Broström, A., & Cai, J. (2020). Promoting academic engagement: University context and individual characteristics. *The Journal of Technology Transfer*, *45*, 304–337.