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The impact of funding on the 5G innovation ecosystem

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Abstract
This paper aims to extend the literature on the impact of research funding. Using 5G as a case study, this paper analyses how funding impacts the 5G innovation ecosystem. Using the functions of innovation systems as a framework, we analyse how several of these functions are influenced by research funding. The results a portion of the ecosystem only participates with funding. In addition the structure of the ecosystem is significantly altered. Research topics are also influenced by funding: some being mostly treated through funding. Funding has little to no impact on the publications that lead to patents.

Keywords Innovation ecosystem · 5G · Impact of funding · Scientometrics · Bibliometrics

Introduction

Funding agencies play a central role in innovation ecosystems. Through their funding schemes, they aim to support research and innovation to achieve economic growth and work towards societal goals. Given the extensive funding efforts worldwide, the question whether funding achieves its impact has been extensively studied. A large focus has been on the quality of research outputs and the productivity of researchers (Ebadi & Schiffauerova, 2016; Chevalier et al., 2020; Gök et al., 2016; Jacob & Lefgren, 2011), collaborations have received less attention (Hicks et al., 2019). The impact of specific funding programs has also received attention (Kanda et al., 2019; Keller & Block, 2013). While these dimensions are vital to understand how funding impacts innovation, a systemic view can provide even more insight. Innovations emerge and evolve in an ecosystem of players, each contribution in one way or another to the innovation process. Funding can therefore have an impact beyond the funded players.

This systemic view of innovation has led to new demands from policy-makers to better understand the innovation systems and how to build systemic impact with funding (Sagar & Holdren, 2002). Funding agencies do not only play an important role to favor innovation, they are an integrate part of the innovation system. A lack of understanding of this system limits the resource allocation process they are in charge of and might result in sub-optimal

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decisions. In this paper, we therefore aim to extend the literature on the impact of funding by analysing the impact of research funding on the level of the innovation ecosystem.

To frame the analysis, we follow the functions of innovation systems identified by Hekkert et al. (2007). The authors identify seven main functions for an innovation system, from which we will study the first 3: (1) The creation of knowledge, (2) the diffusion of knowledge, (3) the orientation of the search. The functions we won't treat in this paper are linked to dimensions we cannot measure with our data (financial and human resources, markets, and entrepreneurship). We focus in this paper on the research level of the system.

Our use case will be the fifth generation of mobile network, commonly known as 5G. 5G marks a radical technological improvement over its predecessor. While 4G is seen as an incremental improvement on 3G, 5G has the potential to heavily impact industry and create new markets (Pujol et al., 2016). Beyond faster download speeds, 5G unlocks the possibility for objects to connect over the internet, providing a wide range of applications (Andrews et al., 2014; Talwar, 2017). The Internet of Things (IoT) allows for communication and control of objects containing sensors over a wireless network. The applications are numerous and touch majors sectors such as healthcare, automotive, and agriculture. The impact on the economy overall is therefore expected to be significant (Campbell et al., 2017) and the competitive pressure for companies is high. Because of this, funding into 5G technologies has been extensive which makes for an interesting case study.

The rest of this paper is organised as follows, the first section presents the data and methodology. The second section presents the results of the analysis, the final section concludes.

Data and methodology

Data

The data for this analysis comes from the Scopus database. Relevant publications are identified by building a query which was discussed with experts and adjusted according to their feedback.[1] Books and literature review are excluded since we focus on technological developments and capabilities of players (Bem, 2016; Sendstad, 2012). In addition, books and reviews attract more citations which might bias citation-based indicators which are often used for quality measurements (Miranda & Garcia-Carpintero, 2018). Furthermore, we restrict the analysis on the domains of computer science, engineering, mathematics, and materials science to focus on core technologies. With the query and the constraints, we identify 24253 scientific publications, worldwide, between 2010 and 2021.

From the publications in the sample we extract the affiliations, citations, funding acknowledgements and the abstracts. Affiliations were cleaned[2] and aggregated at the level of the institution. i.e. any departments were removed and replaced by the overarching company.

Citations are extracted from the papers and aggregated at the affiliation level to measure knowledge flows between players. In order to assess the flow of knowledge from research

[1] The final query is presented in the appendix.

[2] A combination of OpenRefine (https://openrefine.org/docs), and custom R scripts were used as well as some manual checking.

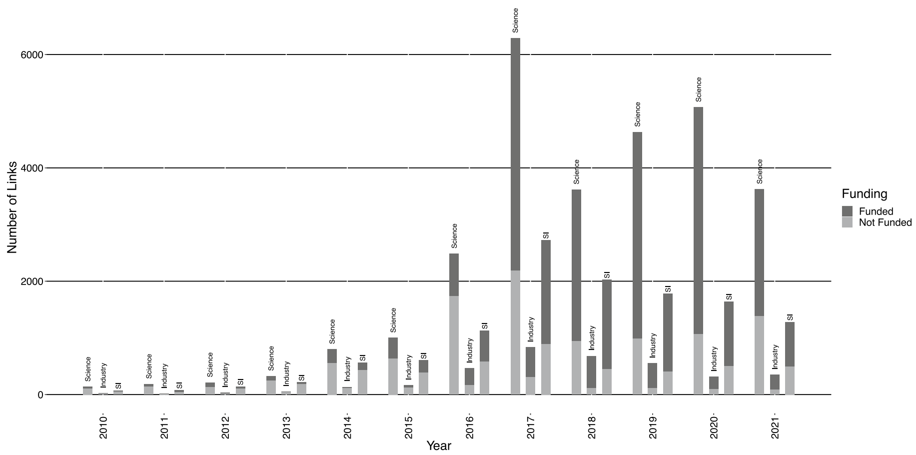


Fig. 1 Evolution of the number of papers per type of player according to funding. Science refers to papers without a corporate player, Industry refers to players with only corporate players, and SI is a mix of Science and Industry players. A paper is considered funded when the author acknowledge a source of funding. *Source* Scopus, treatment: Author

to industry we complement the publications with Patent citation information using the lens.org database.[3] Affiliation names are harmonised between these datasets with the aforementioned method.

Policy instruments often incentivise Science-Industry relations. To allow us to include this in the analysis we tag the affiliations on the papers in one of two categories: "Science" for research institutions, "Industry" for all others. This allows us to categorise papers into one of three categories: (1) *Science*, implying that no corporate players are on the paper, (2) *Industry*, Implying that only Corporate players are on the paper, (3) *SI*, implying that at least one of the players is Industry and one is Science type.

To identify funded publications, the acknowledgements section of the papers is analysed. This data point is widely used but has some limits (Álvarez-Bornstein & Montesi, 2020; Paul-Hus & Desrochers, 2019). Since this section of the paper is often open-format, the information is not standardised and can contain a variety of information. We used text mining techniques to extract funder information.[4] A publication is considered funded whenever there is a funder acknowledged in the section. After treatment of the acknowledgements section, we identify 11549 publications with declared funding and 12704 without (Figs. 1, 2).

[3] https://www.lens.org. This database covers 144.3 million patents and 4.7 million citations between patents and publications.

[4] We searched for funders and not funding numbers since different projects can have the same number with different funders.

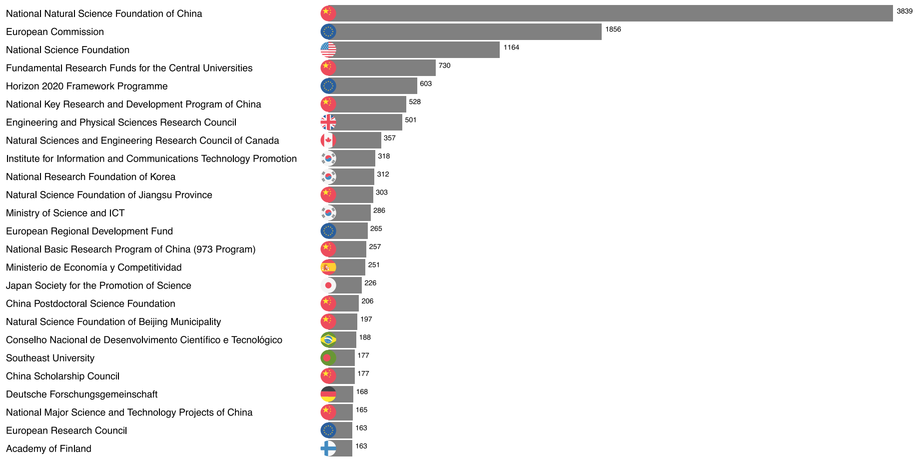


Fig. 2 Number of publications per funding source. *Source* Scopus, Treatment: Author

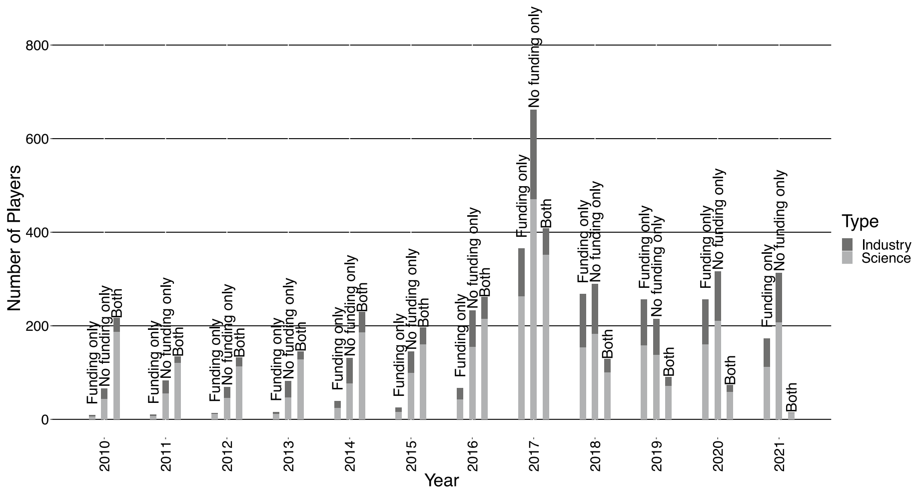


Fig. 3 Evolution of the number of players by year of entry in the system. The players are classified according to their link with funding. Players that exclusively publish with funding are noted "funding only", those that never declare funding "No funding only" and those that have both are noted "Both". The classification relates to the whole period. *Source* Scopus. Treatment: Author

Data description

From this dataset we can produce the dynamics of the number of scientific publications presented in Fig. 3. For each year, the number of papers by category is presented, according the funding.

There is an overall increase in the number of papers during the period, with only limited funding in the first half. In 2016, the number starts to increase more significantly with 2017 marking the peak. Several factors can explain this dynamic. First, the 5G standard plays a central role. research is required both for the definition of the technological specifications of the standard and for finding the technological solutions. Research that does not meet the specifications will be of less value. There is a clear increase in scientific production once the first elements of the standard are known. This also sparks new funding schemes, for China, 2016 marks the start of the 13th 5-year plan(Development & Commission, 2016), and the first Private Public Partnerships are started in Europe.

Science-Industry (SI) papers take off slowly, and switch from majorly unfunded to majorly funded around the 2017 tipping point. Corporate players search for solutions that comply with standards, their absence in the first period is therefore not a surprise. An absence of publications does not imply an absence of presence. Telecommunication technologies evolve continuously, it is therefore likely that the companies still work with the research institutes and observe the evolution of the technology without actively publishing.

The acknowledgement in the papers allow us to identify a variety of funding sources. The overwhelming majority of these sources are public. In fact, the major industrial players are the only ones acknowledged and only in a handful of papers.

Figure 2 shows the top 20 funding entities in the dataset. Note that the European Commission and "Horizon 2020 framework" are separate entries. This is because we base the identifications on the written acknowledgement of the authors. In certain cases "European Commission" is the only information provided, but this does not mean the funding came through the H2020 framework. We therefore keep the information as close to what was provided as possible. However, when both are mentioned in the acknowledgements, lowest level of aggregation is kept.

The barpot shows funding agencies from the largest economies in the world, with India missing (even though India played an important role in the 5G standard). China has a large array of funding instruments for 5G and communication technologies, while Europe and the US have a more focused approach.

The analysis mixes different and asynchronous funding schemes. China usually works on 5-year plans, the EU works according to their frameworks (FP7, Horizon 2020, Horizon Europe), while the National Science foundation has a continuous bottom-up approach. This means that we analyse the impact of funding in a general, worldwide, setting without focusing on the impact of one specific instrument.

Methodology

Using this dataset, we will compute different types of indicators that relate to either one or multiple functions of Technological Innovation Systems. Table 1 summarises the different functions and the measures we will put in place to analyse the impact as proposed by Hekkert et al. (2007). For the last 3 functions however, we have no available data to come to any valuable conclusion. We will leave these dimensions for a later paper. For now, we focus on the first four functions covering the creation of knowledge to the diffusion of this knowledge to industry.

The first function of the innovation system focuses on how knowledge is created in the TIS. New knowledge is the result of the recombination of existing knowledge (Schumpeter, 1942). This means that policy instruments can influence knowledge creation by providing ways to improve the flow of knowledge within the system (Autant-Bernard et al., 2013; O'Mahony & Vecchi, 2009; Sena, 2004). The latter can be achieved through providing funding to access tools and resources to perform research, integrate new players, and facilitate collaboration. A first method to measure these effects is by analysing the number of

Table 1 Functions of the TIS and measures used to assess the impact of funding per function. Adapted from Hekkert et al. (2007)

Functions	Definition	Measures
1. Knowledge creation	Generate the knowledge required for the technology to emerge and evolve	New players, number of players and typology number of publications quality measured by the FWCI
2. Knowledge diffusion	Ensure the appropriate diffusion of the knowledge related to the technology	Science-industry links number of links structure of the network patent citations
3. Orientation	Orient the trajectory of the technology	Funded topics funding agencies and companies
4. Resistance to change	How the technology finds its position in the incumbent system	*Not adressed*
5. Resource	How financial and human capital are used to develop the technology	*Not adressed*
6. Market	Help technologies find new markets	*Not adressed*
7. Entrepreneurs	Generate and take advantage of, new business opportunities	*Not adressed*

players in the system and the number of new players entering the system. The impact of funding can then by analysed by measuring the number of player that entered the system only through funding, those that never received funding and those that had a hybrid position.

The typology of the players also plays an important role. *In fine*, the aim of research in the 5G setting is to promote industrial innovation to achieve economic growth (Anić 2017; OECD. 2016). The inclusion of industrial players in the innovation process is therefore important. Interactions with science have shown a positive impact on industrial players (Levy et al., 2009) by allowing for more diversity in their knowledge sources (Kaufmann & Tödtling, 2001) it is also their preferred method of knowledge transfer (Cohen et al., 2002). For this reason, we track the number of industrial players and the links they create in the system through funding (Guimón & Paunov, 2019). The presence of these players is not only beneficial for the corporate players themselves but also for the science players who extract knowledge useful for their research from the collaborations (Lee, 2000; D'este & Perkmann, 2011). For these reasons we analyse the number of industrial players in the system a relate their presence to funding.

These measures complement the more traditional indicators of the number of publications and their citation-based quality measures. We will use the Forward Weighted Citation Impact indicator to assess differences in quality between funded and unfunded research. This measure normalises the citations according to the year of publication of the paper as well as the domain in which it was published.[5]

These latter points are closely related to the second function which is knowledge diffusion. The efficient diffusion of knowledge in the system impacts the efficiency of the system itself. The more knowledge flows, the faster it spreads, the more potential it has to reach other players who might use this knowledge again to innovate (Rogers, 1995). Measuring the impact of funding on the dimension of diffusion will be done through 2 lenses. A first will focus on the collaboration network between the players, with a focus on the overall structure and a focus on the structural position of industrial players. For this purpose we will perform a descriptive network analysis to assess how funding have changed the structure of the system. A second will focus on citations, both between papers and from patents, once again to zoom in on the transfer to industry.

When we look at the third dimension, orientation, we can raise the question whether the players in the system perform their research on the same topics when they receive funding as when they don't. To assess this element we will perform a textual analysis of the abstracts of the publications, differentiating between funded and unfunded publications. We will create a co-occurrence network of the extracted terms and cluster them into topics. We then analyse the proportion of funded and unfunded papers for each topic. In addition, an analysis of the funding agencies and schemes also sheds light on the orientation of the search by funding institutions.

[5] The Scival definition: "Field-Weighted Citation Impact (FWCI) in SciVal indicates how the number of citations received by an entity's publications compares with the average number of citations received by all other similar publications in the data universe. Similar publications are those publications in the Scopus database that have the same publication year, publication type, and discipline, as represented by the Scopus journal classification system. The discipline is defined by the Scopus ASJCs given to an article via the journal in which it is published."

Analysis

Impact on knowledge creation and diffusion

Players and typology

A first impact we observe from funding is the adage of new players in the system. We tag all players in the system according to their type (Science or Industry) and then check whether they published funded papers. This allows us to further identify players that have only published with funding, not published with funding, or a combination of both. The dates are the first year of entry in the system, the typology is fixed over the whole period. In other words, a player tagged as *funding only* in 2010, has entered the system in 2010 and has only published with funding until the end of the period.

In Fig. 3 we show the first year of entry of the players as well as their type. The *funding only* type represents a significant number of players, with number close to unfunded players for some years. Overall, 24.4% of players entered the system on funding alone. For the hybrid players, 31% of players entered the system with a funded publication before they published publications without. The subsequent unfunded publication came within 2 years for 83% of the players. This observation could reflect that players wait for funding opportunities.

Corporate players represent 28% of the players and enter the system for the majority after 2016. This can be related to the specification of the standard at that time. The absence of publications does not *de facto* mean that they are not present in the system. However, their formal implication in research appears to emerge at that point in time.

In total, 536 players are present through funding alone, 877 never publish with funding and 327 do both.

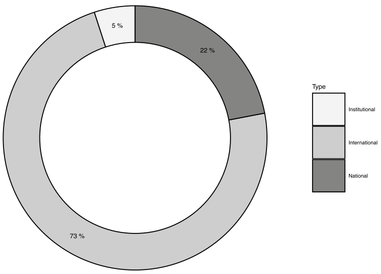
Even though the overwhelming majority of publications received funding during the second period, we do not see this being translated into a large number of new only-funded players in the system.

The increase in size of the system (and potentially the diversity of knowledge therein) is not the only factor that can be beneficial for the creation of knowledge. If we consider that creating new knowledge requires the combination of existing knowledge, then the flow of knowledge through the system has an important role to play. One way with which knowledge flows in the system is through collaboration. The importance of knowledge flows is why it is a specific function for the system. For our purpose, knowledge flows touch both the question of knowledge creation and the dimension of knowledge flows.

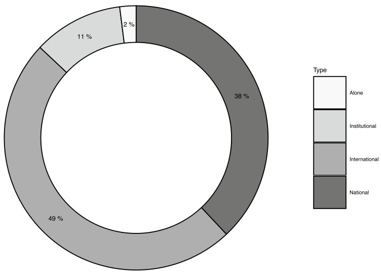
Collaborations

The co-creation of knowledge is a central aspect of the innovation process. Collaboration allows for different players to combine their knowledge. During this process knowledge can flow between the players.

Funding schemes often incentivise different levels of collaboration, some aiming to create links with specific countries or between players at the national level. To analyse the effects of this, we differentiate between different levels of collaboration. In Fig. 4 we show the percentage of collaborations between national players (*national collaboration*), between players from different countries (*International collaboration*), between



(a) Number of papers per collaboration type for funded papers.



(b) Number of papers per collaboration type for unfunded papers.

Fig. 4 Collaboration statistics for funded and unfunded papers. *Source* Scopus/Scival, Treatment: Author

authors from the same institution (*Institutional collaboration*), and finally, papers written by single author (*alone*).

Collaboration is therefore at the center of funding schemes. We observe no funded papers with a single author, this number is also low for unfunded papers. However, we observe a significant difference in the typology of the other types. More international collaboration and less national and institutional collaboration for unfunded papers. The European framework is here a clear factor, incentivising collaboration between countries of the European union to favour knowledge flows and competitiveness of European companies. The same type of strategy is implemented by China and the US.

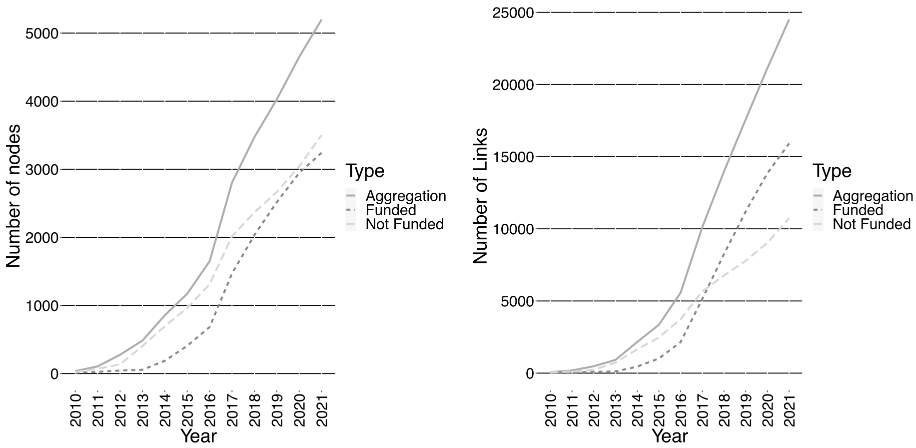
The structure of the networks allows to gain insight into the diffusion of knowledge in a more detailed manner. We create a network between the affiliations of the authors of the papers. Depending on how players in the system are connected, knowledge can flow more or less efficiently through the system (Cowan & Jonard, 2007; Verspagen & Duysters, 2004).To have a more precise view of the impact of funding on collaboration, we analyse the structure of the network between the players. We follow a methodology close that that of Hicks et al. (2019).

The overall network contains 5200 players and 24510 unique collaborations. This means that on average, each player has 9.42 collaborators and 16.9 co-authored papers.

For each link in the network we identify if the collaborations are funded. As we did for the players, we then identify collaboration that are always, never, or sometimes funded.

Results shows that 55.43% of all links in the network are only supported by funded papers. 35.37% of the links never publish with funding. This shows that even though the number of players that entered the network exclusively with funding was not high, the impact on collaboration with funding is much more extensive. To improve our view of the structural impact of these links, we will analyse the structure of three networks. The first two are subsets of the complete network. A first is build from only the funded papers, a second with unfunded papers. The third network is build from the entire set.

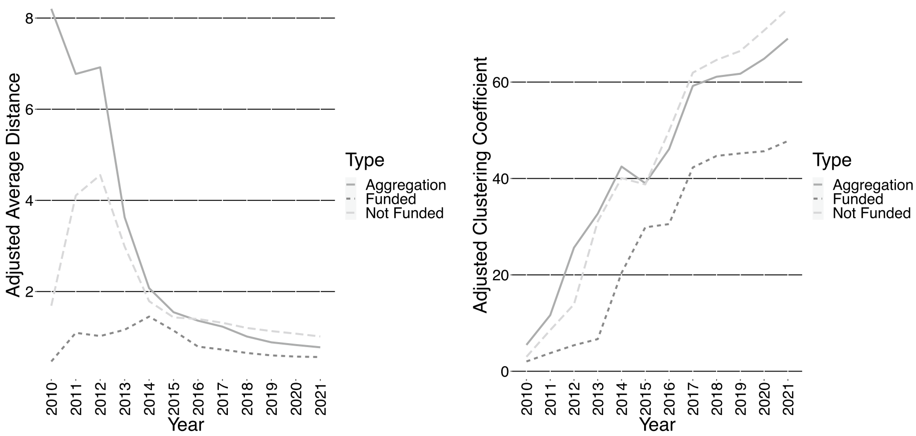
In Fig. 5a and b we show the evolution of the dimensions of the network. The funded network takes more time to structure. Reflecting the dynamics of funded publications. The number of funded players remain inferior to the number of unfunded players. A comparison of the players shows that 1366 players are exclusively present in the funded network and 1615 exclusively in the unfunded network. The networks do not only differ in size but also in terms of who is present.



(a) Evolution of the number of nodes

(b) Evolution of the number of links

Fig. 5 The evolution of the dimensions of the network. In **a** the evolution of the number of players (nodes) in the network, in **b** the evolution of the number of links (collaborations) *Source* Scopus, Treatment: Authors



(a) Evolution of the average distance

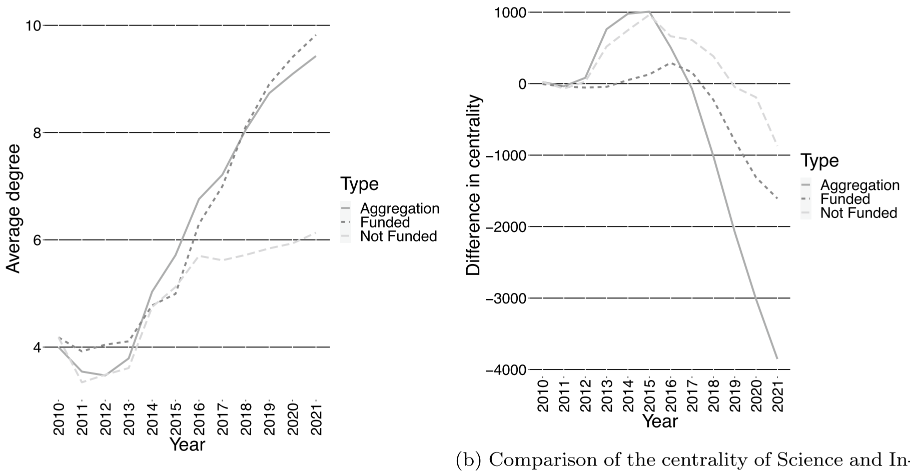
(b) Evolution of clustering

Fig. 6 Evolution of the average distance and the clustering of the network

When it comes to links however, the funded network overtakes the unfunded network in 2017, this trend continues until the end of the period. As a result the funded network presents a higher density.

Funding incentivises collaboration while at the same time creating a contractual context that reduces the risk for free-riders. This results in the impact we observe, a more densely connected eco-system compared to the unfunded network (Fig. 6).

From a knowledge diffusion perspective, the distance between the players and their clustering plays an important role. Diffusion requires players to be at a low distance from



(a) Evolution of the average degree

(b) Comparison of the centrality of Science and Industry Players

Fig. 7 Network statistics of the collaboration network

one another, while being locally densely connected. The rationale is that players combine knowledge locally with well established connections and then diffuse this knowledge through to other communities (Watts, 1999). From a network perspective this means that we are interested in the average distance between the nodes as well as the clustering coefficient.[6]

The average distance shows that the funded network maintains a low average distance over the period. This shows the positive potential for rapid transfer of knowledge in the network. In contrast, the average distance of the unfunded network is much higher and takes longer to converge to lower levels. At the beginning of the period, the network was only sparsely connected. It was build up from loosely connected, dense communities. As these communities slowly connect the distance reduces. Funding accelerates this process, with a direct impact on the structure of the system.

Clustering shows that the funded network is less clustered than the unfunded network. This confirms our previous observations that funding opens the network to new players, resulting in less clusters. The unfunded network is build from players that appear to work in clusters that are less closely connected. Unfunded players work with the same players with only a few connections between the clusters. This hypothesis is further corroborated by the difference in average degree between the two networks. The unfunded network has a low average degree, highlighting that those players collaborate with a few, highly clustered players, with low distance between the clusters. The funded network however, shows to have a very high average degree, putting forth the impact of funding on the diversity of players and the diffusion of knowledge between them.

The diffusion argument strengthened by the presence of a small world structure characteristics (adjusted clustering $>> 1$ and adjusted average distance ≈ 1) (Gulati et al., 2012). This structure is recognised as being efficient for the diffusion of knowledge for innovation

[6] Since we are working in a dynamic setting we adjust the indicators according to Gulati et al. (2012). This method adjusts for the size of the network removing any distortions.

(Verspagen & Duysters, 2004). The network satisfies the conditions around the year 2017, mainly through the additional links through funding (Fig. 7).

The role of industrial players

Funding focuses on the role of industry in the system. We therefore look at the position of industry players in the network. In Fig. 7 we represent the difference between the average centrality scores of Science and Industry players. Whenever the line is above 0, this means that the centrality of Industrial players is higher than that of Science players. The inverse is true when the values reaches below 0. The results show that in the early stages, industrial players have a more central position than science players. This shows that the players connecting different communities in the sparse network are in fact, corporate players. As the network densifies with the entry of more science players, industrial players are pushed to less central positions. However, the Science-Industry links that are of interest for knowledge flows, are on average more central than the other links. In fact, Industry-Industry links are the less central (Centrality of 1471), while SI links have a centrality score of 2404.[7]

Citations

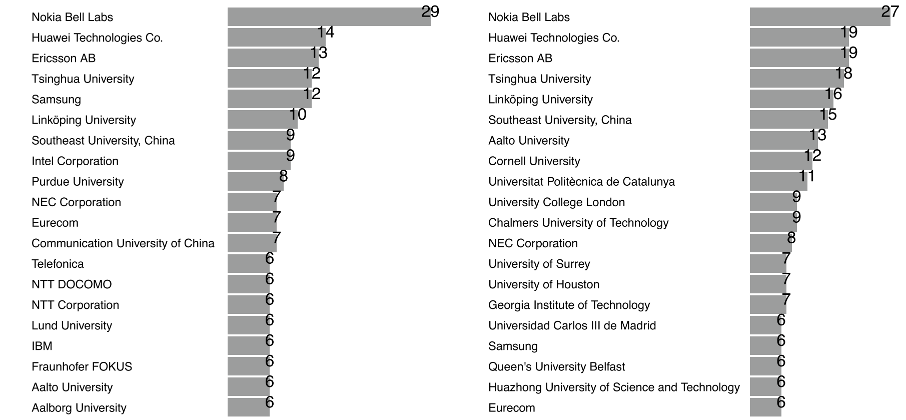
While collaboration can be considered a potential for knowledge flows, citations can be used as a more direct measure (Tsay, 2015). Using citations we can analyse 3 dimensions of knowledge flows, first we have a direct vision of citations between papers, we can aggregate this information at the level of the affiliations to create a measure of knowledge flows between players. Finally, we use citations to identify which patents are citing the publications, showing proof of knowledge flows to industry.

In this part of the analysis, the number of players is reduced significantly. Many of the players with publications, do not receive any citations. 1747 players are cited, with 16995 citation links. 81% are science players while 19% are industry players. On average, the industrial player receive 11.77 citations while the science players receive 9.28.

Citation concentration To measure a difference in citations between funded and unfunded papers, we look at how many different players cite publications on average. In other words, we count the number of different affiliations on the citing publications of each document. From this perspective, there is little difference between funded and unfunded papers. On average the funded papers have 5.46 different affiliations citing, while the unfunded papers have 5.91 players citing. There is no significant difference for funding when differentiating papers written by corporate players or science players (2.53/2.74 for industry players and 4.77/5.09 for science players). Funding apart, the results show that on average the science players are cited by almost twice as many players. The papers have a different scope in terms of diffusion. The papers written by industry players appear to be cited more intensely, but by less players. Science papers diffuse more broadly while the industry papers are of interest to a more restricted group of players (possibly industry players themselves).

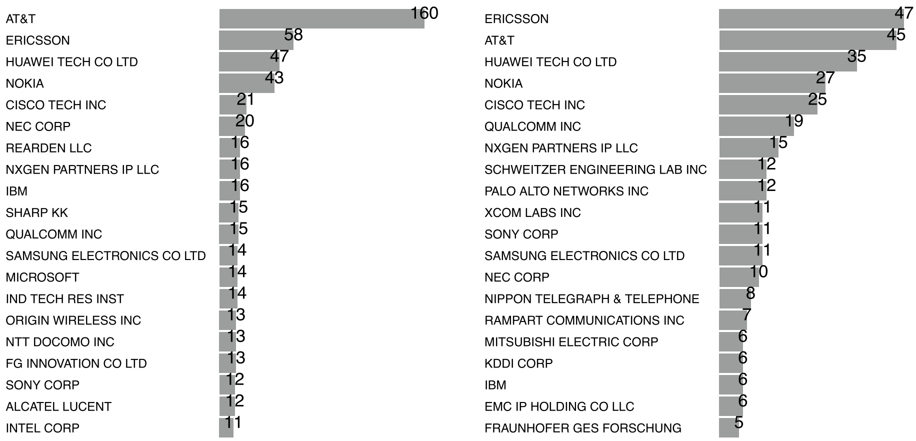
Diffusion to industry While citations between papers reflect how player diffuse and absorb knowledge for the purpose of research, citations from patents show how this

[7] We use link betweenness centrality.



(a) Players cited by patents for unfunded publications (b) Players cited by patents for funded publications

Fig. 8 Barplot of the number of patent citations received by players



(a) Assignees citing unfunded publications (b) Assignees citing the funded publications

Fig. 9 Barplot of the number of citing patents per player

research results in new technical solutions. Analysing these citations hence shows a more direct link of the impact of research to potential economic growth.

We find 309 funded publications cited by 889 patents, while 351 unfunded publications are cited by 1558 patents. It is interesting to note that between the two sets of citing patents only have a 6.8% overlap. The unfunded publications receive twice as many patent citations, from mainly different patents. The difference could be explained by the idea that the publications sets treat different topics. We will check this later on in the paper.

Among the cited and funded publications, 35% are Science-industry papers, against 28% for unfunded papers. This is in contrast with the 18% of overall SI publications in the set. With only 3.6% being Industry only papers, most of the citations are concentrated on a small number of industrial links (and players). Figures 8 and 9 show the top affiliations from the cited publications and the top assignees from the citing patents. These barplots show the clear concentration of citations on the level of the affiliations. Even though there are overall more citations for Science-only publications, we see that the concentration is higher for industrial players. This is the case for both funded and unfunded papers. Hence we do not see a clear impact of funding here other than a higher SI citation number.

We note in addition, that the number of citing patents for the unfunded publications is highly influenced by AT &T, citing a large number of publications with its patents.

When it comes to knowledge diffusion, funding has little impact on the diversity of the citing players. Even though the citations to science only papers are larger in number, they are more spread out at the level of the affiliations. There are less SI citations but there are more clustered on a small number of affiliations. Funding does not appear to have an influence here.

Quality

In this final part of the knowledge related dimensions, we aim to analyse the impact of funding on the "quality" of research produced. 38.9% of funded papers are published in top journals, against 22.9% for unfunded papers.[8] This shows a clear difference in terms of quality at the journal level. At the level of the publications this is less the case. If we look at the FWCI[9] we can measure the impact of a publication. For funded publications the FWCI is 2.07, while unfunded publications have a FWCI of 1.84. In other words, the funded publications attract a little more than twice the citations than other publications in the same domain the same year, against 1.84 for the unfunded publications. The difference is less substantial than at the journal level.

With a heavy focus of policy on the importance of science industry links, we can focus on the impact of the SI publications specifically. The effects are inverted here, unfunded publications have a FWCI of 3.1 while funded publications have 2.84. Nevertheless, the SI publications have a higher impact on average than publications with no corporate player involved (1.96 and 1.7). This means that the idea that corporate player play an important role in the creation of knowledge is justified, however, funding is not accentuating this impact. The apparent opposition between the top journal statistics and the publication level FWCI, can be explained by the scope of the research. If the research published by corporate player is more broad this might attract more citations. It would be rational for a corporate player to not publish from it's own accord research on a specific area that could cost its competitive advantage. In the setting of a funded research project, the corporate player could have a more focused role resulting in more specific research attracting less citations.

For the other types of collaborations (national and international) the difference in the FWCI is marginal while the values remain above 1 for both dimensions. International collaboration has the highest values at 2.83 and 2.89 for funded and unfunded publications

[8] The most-cited journals are defined by the journal metrics CiteScore, SNIP (Source-Normalized Impact per Paper) or SJR (SCImago Journal Rank). This means that the data universe is the set of items indexed by Scopus that have a journal metric and so can be organised into percentiles; this excludes publications in stand-alone books and trade publications, which do not have journal metrics.

[9] Field-Weighted Citation Impact (FWCI) in SciVal indicates how the number of citations received by an entity's publications compares with the average number of citations received by all other similar publications in the data universe: how do the citations received by this entity's publications compare with the world average?. Similar publications are those publications in the Scopus database that have the same publication year, publication type, and discipline, as represented by the Scopus journal classification system. The discipline is defined by the Scopus ASJCs given to an article via the journal in which it is published.

respectively. Open-access has an overall positive impact on the FWCI on all dimensions, clearly showing that the impact on the diffusion of knowledge.

Orientation of the search

Research in 5G technologies is influenced by different forces. As a technology that is subject to standardisation, research aims to provide technical solutions that do or can reach the technological specifications. The agents behind the setting of this standard are for a large majority the corporate players. The latter then influence research already by playing a central role in the setting of the standard.

Funding agencies themselves orient the search by prioritising different avenues of research. These are often based on citizen concerns or societal challenges that need to be taken into account (less energy consumption, less rate earth minerals, less radiation). These elements still need to comply to the standards set by the agencies (ETSI, 3GPP).

The funding of 5G research is not entirely set by the funding agencies on their own. The industrial expertise remains with the corporate players and hence, they are often included in the definition of priorities and what the technology is actually capable of. A striking example are the European Public Private Partnerships (PPP). These contracts are the results of discussion between the 5GIA (the 5G Infrastructure Association) in which corporate player organise themselves to negotiate with the European Union to fix priorities.

The role of industrial players is central in the entire process, since in the end it's the industrial applications that will create the anticipated growth. As such, research that results in a high performance technology, but lacks the characteristics to be economically viable, might be a waste of energy. The central position of corporate players in the ecosystem is therefore not accidental. They benefit greatly from being the firsts to see how the technology is developing to reach a fast time-to-market.

While funding plays a the role of an enabler to push the technology further and directs the technology to meet more societal challenges, firms orient towards economically viable solutions. We also have to keep in mind that a major aim for firms is to patent any technological solution that relates to a norm. The faster they are able to secure patents on these technologies the larger the potential licensing fees. The increased presence of industrial player on publication from the moment the first directions for the standard emerge and the governmental directions are given are a reflexion of this.

to make an attempt at measuring the impact of funding on the orientation of research, we analyse topics with the help of text mining. The idea is that topics in funded publications differ from those in unfunded publications. We take the abstracts of the identified publications we can extract technical terms and group them into topics. The basic idea here is to start with the extraction of relevant terms, those that appear more than expected in the publication set and then compute the co-occurrences of these terms inside the abstracts. When the co-occurrence deviate from what would be expected in a random distribution, we keep the link. The results presented here were computed in Cortext Manager (Breucker et al., 2016), using the pigeon-hole indicator for the terms and the χ^2 indicator for the links. The resulting network of terms is then clustered using the Louvain method (Blondel et al., 2008). We check to what extend the topics rely on funded publications (Kessler, 2017). In Fig. 10 we show the results of this analysis. Whenever a topic is equally treated by publications that have received funding and not, the topic is positioned on the diagonal. The more the topic is treated by either funder or unfunded publications the more it moves away from the diagonal.

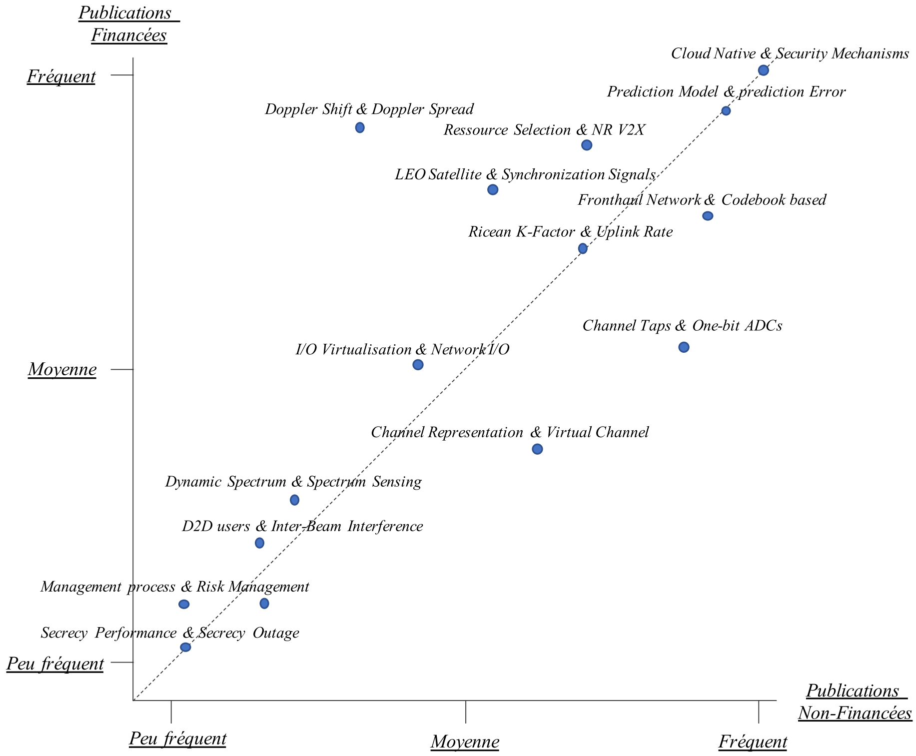


Fig. 10 Differences in topics at the level of the world. *Source* Scopus, Treatment: Authors, using Cortext Manager

For instance, the topic "Doppler shift & Doppler Spread" emerges from a larger proportion of funded publications. While "Channel Taps & One-bit ADS's" has a larger number of publications without funding.

Overall, the topics are quite well aligned. We do observe some topics that attract more funding worldwide. Interestingly, the topics that gravitate towards more funding, have more industrial players involved than those that do not. The publications on these topics have an overall higher concentration of science-industry and industry papers than the average of the dataset.

This shows that at there appears to be an alignment between funding and the orientation industry is looking for. This makes sense since one of the aims for policy instruments is to create economic growth by creating ground for companies to innovate using the fundamental knowledge created in the system. The point shows a link between funding and its impact on industry. We know that industrial players lobby for the orientation of the evolution of the technology. At the European level, the PPP emerge from discussions between what the EC wants for its citizens and what Industry says is feasible. The topics here show that industrial player position themselves on specific topics and manage to attract funding as well. This already informs us to some extend about the orientation of the search which is the third function of the TIS we are analysing.

Conclusion

The aim of this paper is the analysis of the impact of funding on the research system for 5G technologies. To guide this analysis we have analysed different functions of the TIS framework.

We have shown that funding plays an important role in attracting players into the system and in the creation of links between the players. The addition of the funded links have a significant impact on the structure of the network of collaborations and hence on the flow of knowledge in the system.

Corporate players play a central role in the development of the technology as they are present in important positions inside the system. This results in links between science and industry players that remain central in the network and allow for knowledge to flow from research to industrial applications. We have shown that these flows exist, and are clustered around publications authored with the implication of companies.

In terms of research quality, funding has a positive effect. However, science-industry links have a higher impact when unfunded.

The role of industry continues as they influence also the topics analysed. Funded publications contain topics that are less discussed in unfunded papers. In addition, these topics contain more corporate players than the other topics.

In the 5G case, funding plays a significant role in the structuring of the innovation system. The network structure alone is deeply altered with the addition of funded links. However, we cannot state that the network would be fundamentally different without funding. Is is possible that some of the links would have been created without the support of funding. It is nevertheless unlikely that this would have happened for all links. Given the strategic importance of the technology, companies and research institutes know that funding will arrive at some point, it is therefor possible that they wait as to not waste resources that could have been used for other projects.

Our data is a mix of many policy instruments, with close (but different) objectives and timelines. The purpose of this study is to provide an overall view, however studies at the instrument or regional level can shed more light into microlevel strategies and impacts for players.

Appendix

Scopus query

Query for the Scopus Database, executed in october of 2021:

((TITLE-ABS-KEY ((multi-access W/1 edge W/1 computing) OR (milimeter W/1 wave W/1 transmission) OR (mm-wave W/1 transmission) OR (non-ip AND networking) OR (network W/1 virtualisation) OR (network W/1 function* W/1 virtualisation) OR (massive W/1 multi?input W/1 multi?output) OR (massive W/1 mimo) OR (network W/1 slicing) OR (new W/1 radio)) OR (TITLE-ABS-KEY (5G) AND (TITLE-ABS-KEY ((network AND functions AND virtualization) OR (nfv) OR (mec) OR (mwt) OR (non-ip AND networking) OR (nin) OR (small W/1 cells*))))) AND NOT (TITLE-ABS-KEY (nuclear OR cyclotron OR tokamak))) AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020)

OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018) OR LIMIT-TO (PUBYEAR, 2017) OR LIMIT-TO (PUBYEAR, 2016) OR LIMIT-TO (PUBYEAR, 2015) OR LIMIT-TO (PUBYEAR, 2014) OR LIMIT-TO (PUBYEAR, 2013) OR LIMIT-TO (PUBYEAR, 2012) OR LIMIT-TO (PUBYEAR, 2011) OR LIMIT-TO (PUBYEAR, 2010)) AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SUBJAREA, "comp") OR LIMIT-TO (SUBJAREA, "engi") OR LIMIT-TO (SUBJAREA, "math")).

Data sets

See Fig. 11.

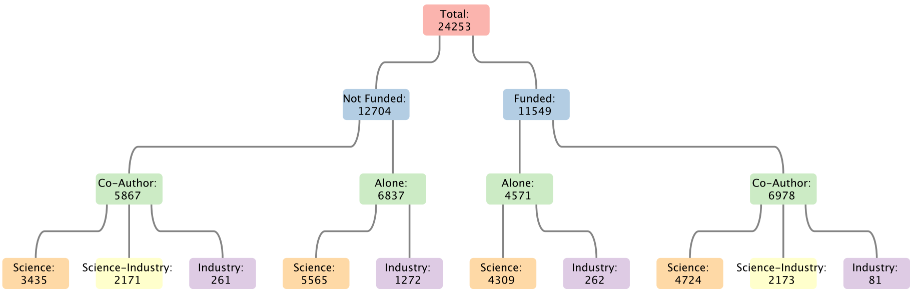
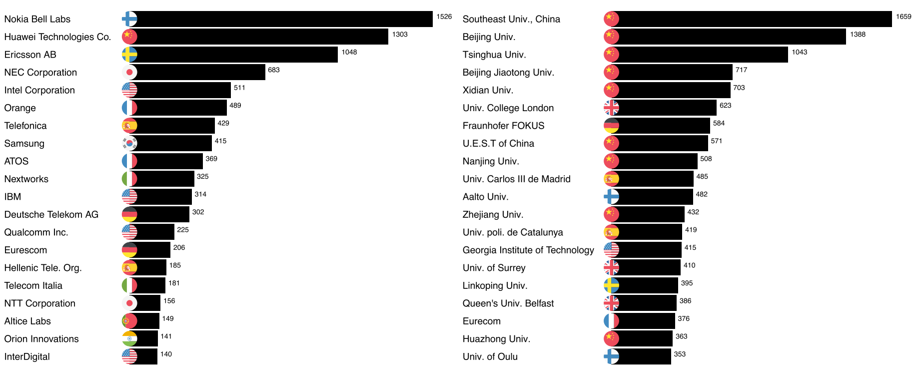


Fig. 11 General Statistics of the publications, according to the origin, co-authorship and funding. For instance the number in the lower left cell states that there are 3435 publications with no funding co-authored by Research Institutions only. In total there are 12704 unfunded publications, from which 6837 are written by one institution from which 1272 are written by corporations

Top players

See Fig. 12.



(a) Top 20 of private players (b) Top 20 of research institutions

Fig. 12 Top players in terms of publications in 5G

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References

Álvarez-Bornstein, B., & Montesi, M. (2020). Funding acknowledgements in scientific publications: A literature review. *Research Evaluation, 29*(4), 469–488.

Andrews, J. G., Buzzi, S., Choi, W., Hanly, S. V., Lozano, A., Soong, A. C., & Zhang, J. C. (2014). What will 5G be? *IEEE Journal on Selected Areas in Communications, 32*(6), 1065–1082.

Anić, I.-D. (2017). Facilitating effective science-industry collaborative research: A literature review. *Privredna kretanja i ekonomska politika, 26*(1 (140)), 7–41.

Autant-Bernard, C., Fadairo, M., & Massard, N. (2013). Knowledge diffusion and innovation policies within the European regions: Challenges based on recent empirical evidence. *Research Policy, 42*(1), 196–210.

Bem, D. J. (2016). Writing a review article for psychological bulletin. *Psychological Bulletin*

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment, 10*, P10008.

Breucker, P., Cointet, J.-P., Hannud Abdo, A., Orsal, G., de Quatrebarbes, C., Duong, T.-K., Martinez, C., Ospina Delgado, J. P., Medina Zuluaga, L. D., Gómez Peña, D. F., Sánchez Castaño, T. A., Marques da Costa, J., Laglil, H., Villard, L., & Barbier, M. (10 2016). Cortext manager. https://docs.cortext.net

Campbell, K., Diffley, J., Flanagan, B., Morelli, B., O'Neil, B., & Sideco, F. (2017). The 5G economy: How 5G technology will contribute to the global economy. *IHS Economics and IHS Technology, 4*, 16.

Chevalier, G., Chomienne, C., Jeanrenaud, N. G., Lane, J., & Ross, M. (2020). A new approach for estimating research impact: An application to French cancer research. *Quantitative Science Studies, 1*(4), 1586–1600.

Cohen, W. M., Nelson, R. R., & Walsh, J. P. (2002). Links and impacts: The influence of public research on industrial R & D. *Management Science, 48*(1), 1–23.

Cowan, R., & Jonard, N. (2007). Structural holes, innovation and the distribution of ideas. *Journal of Economic Interaction and Coordination, 2*(2), 93–110.

D'este, P., & Perkmann, M. (2011). Why do academics engage with industry? The entrepreneurial university and individual motivations. *The Journal of Technology Transfer, 36*(3), 316–339.

Development, N., & Commission, R. (2016). The 13th five-year plan for economic and social development of the people's republic of china (2016–2020). Translated by the Compilation and Translation Bureau, Central Committee of the Communist Party of China.

Ebadi, A., & Schiffauerova, A. (2016). How to boost scientific production? A statistical analysis of research funding and other influencing factors. *Scientometrics, 106*(3), 1093–1116.

Gök, A., Rigby, J., & Shapira, P. (2016). The impact of research funding on scientific outputs: Evidence from six smaller European countries. *Journal of the Association for Information Science and Technology, 67*(3), 715–730.

Guimón, J., & Paunov, C. (2019). *Science-industry knowledge exchange: A mapping of policy instruments and their interactions*. OECD Science, Technology and Industry Policy Papers, No. 66, OECD Publishing, Paris.

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.

Hekkert, M. P., Suurs, R. A., Negro, S. O., Kuhlmann, S., & Smits, R. E. (2007). Functions of innovation systems: A new approach for analysing technological change. *Technological forecasting and social change, 74*(4), 413–432.

Hicks, D. J., Coil, D. A., Stahmer, C. G., & Eisen, J. A. (2019). Network analysis to evaluate the impact of research funding on research community consolidation. *PLoS ONE, 14*(6), e0218273.

Jacob, B. A., & Lefgren, L. (2011). The impact of research grant funding on scientific productivity. *Journal of Public Economics, 95*(9–10), 1168–1177.

Kanda, W., del Río, P., Hjelm, O., & Bienkowska, D. (2019). A technological innovation systems approach to analyse the roles of intermediaries in eco-innovation. *Journal of Cleaner Production, 227*, 1136–1148.

Kaufmann, A., & Tödtling, F. (2001). Science-industry interaction in the process of innovation: The importance of boundary-crossing between systems. *Research Policy, 30*(5), 791–804.

Keller, M. R., & Block, F. (2013). Explaining the transformation in the us innovation system: The impact of a small government program. *Socio-Economic Review, 11*(4), 629–656.

Kessler, J. S. (2017). Scattertext: A browser-based tool for visualizing how corpora differ. arXiv:1703.00565

Lee, Y. S. (2000). The sustainability of university-industry research collaboration: An empirical assessment. *The Journal of Technology Transfer, 25*(2), 111–133.

Levy, R., Roux, P., & Wolff, S. (2009). An analysis of science-industry collaborative patterns in a large European university. *The Journal of Technology Transfer, 34*(1), 1–23.

Miranda, R., & Garcia-Carpintero, E. (2018). Overcitation and overrepresentation of review papers in the most cited papers. *Journal of Informetrics, 12*(4), 1015–1030.

OECD, K. (2016). *OECD science, technology and innovation Outlook 2016*. OECD Publishing.

O'Mahony, M., & Vecchi, M. (2009). R & D, knowledge spillovers and company productivity performance. *Research Policy, 38*(1), 35–44.

Paul-Hus, A., & Desrochers, N. (2019). Acknowledgements are not just thank you notes: A qualitative analysis of acknowledgements content in scientific articles and reviews published in 2015. *PLoS ONE, 14*(12), e0226727.

Pujol, F., Elayoubi, S. E., Markendahl, J., & Salahaldin, L. (2016). Mobile telecommunications ecosystem evolutions with 5G. *Communications & Strategies, 102*, 109.

Rogers, E. M. (1995). *Diffusion of innovations*. Simon and Sschuster.

Sagar, A. D., & Holdren, J. P. (2002). Assessing the global energy innovation system: Some key issues. *Energy Policy, 30*(6), 465–469.

Schumpeter, J. A. (1942). *Capitalism, socialism and democracy*. Routledge.

Sena, V. (2004). Total factor productivity and the spillover hypothesis: Some new evidence. *International Journal of Production Economics, 92*(1), 31–42.

Sendstad, M. (2012). Challenges and opportunities for governing ecosystem services in an urban world: A systematic review and synthesis.

Talwar, S., & Vannithamby, R. (2017). *Towards 5G: Applications, requirements & candidate technologies*. Wiley.

Tsay, M.-Y. (2015). Knowledge flow out of the domain of information science: A bibliometric and citation analysis study. *Scientometrics, 102*(1), 487–502.

Verspagen, B., & Duysters, G. (2004). The small worlds of strategic technology alliances. *Technovation, 24*(7), 563–571.

Watts, D. J. (1999). Networks, dynamics, and the small-world phenomenon 1. *American Journal of Sociology, 105*(2), 493–527.