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A preliminary analysis of knowledge flows: the case of structural composite materials in aeronautics[☆],^{☆☆}

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Abstract

In this paper we study the evolution of the collaboration network of structural composite materials in aeronautics between 1980 and 2013. The network is generated using patent and publication data and analyzed following a macro to micro level methodology. All results and interpretations were discussed and validated by engineers and executives from the relevant sector.

The macro analysis shows that the evolution of the network is correlated with the life-cycle of the technology. During the research phase, the network structure converges towards a small world. The network becomes a small world when the development stage of the technology is reached. At this point the newly developed technologies diffuse. The structure then diverges from the small world structure once the technology has been integrated.

On a micro level the network shows that two diverging strategies in terms of preferential attachment (Barabási and Albert, 1999) lead to a significant difference in terms of innovative performance.

Keywords: knowledge diffusion, collaboration network, patents, publications, bibliometrics, dynamic network

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1. Introduction

Innovations are the driving force behind growing economies and prosperous firms. Achieving innovation is hence at the center of any business strategy. With the growing complexity of new technologies, a single firm can
5 no longer master all the technologies needed for the production of a single product. Accessing knowledge held by other firms becomes of vital importance for firms in order to innovate. Accessing different knowledge sources has proven to be beneficial for the firm McEvily and Marcus (2005), for innovation Kogut and Zander (1992), Tsai (2001) as well as survival and growth
10 Watson (2007).

Working under the Schumpeterian hypothesis that innovations are achieved through the recombination of existing technologies, diversity is the key to new innovations Dosi (2000), Cowan and Jonard (2007). By recombining knowledge held in different firms new knowledge is created.

15 Cooperations started to appear between firms, changing the business landscape by a profound reconsideration of strategic decisions. Firms now focus on the identification of efficient partners in order to absorb and recombine as much relevant information as possible.

Empiric analyses show that the number of cooperations has increased steadily
20 over the last two decades paolo Saviotti (2007). During this same period we can observe that cooperation has evolved from (predominantly) dyadic cooperation to multilateral cooperations. Firms evolve in networks, an interconnection of cooperating firms with a common goal Pippel (2013).

In networks knowledge flows between firms, allowing them to learn from one
25 another. The manner in which firms benefit from the network depends in part on the structure of the network since the structure defines how fast and efficient knowledge flows through the network Verspagen and Duysters (2004).

The evolution of these networks has been studied in the past by many researchers Ahuja (2000), Verspagen and Duysters (2004), Buchmann and Pyka
30 (2013), König et al. (2011), ven der Valk et al. (2011).

We hypothesize that there is a correlation between the evolution of the structure of a collaboration network and that of the technology life-cycle. More precisely, the life-cycle of a technology is defined by a research and a development stage. The structure of the network differs according to the stage
35 of the cycle. A first stage requires the absorption of knowledge from fundamental research and knowledge from other sectors. The second stage is

defined by a diffusion of the new technology. In order to verify this hypothesis we analyze the structure and evolution of the knowledge network relative to structural composite materials. The first aim of this chapter is hence to
40 analyze how a collaboration network evolves when a new technology is being developed.

Since we focus on an existing sector, firms already have collaborative links with other firms. Firms hence need to make the strategic decision to either
45 collaborate with historic partners or collaborate with new firms. The importance of social capital in network evolution has been intensively studied. We present here an example of two firms developing a same technology which took opposite decisions in terms of collaboration. We will show how one strategy resulted in a 10-year technological delay in development. The second aim of this paper is hence to consider the impact of social capital as a
50 collaborator selection mechanism on innovation performance.

This chapter is organized as follows. In a first section we will present the technology under analysis: Structural Composite Materials (SCM). We
55 will then present the data and methodology. Section 3 provides an analysis of the IPC network, section 4 correlates section 3 with the evolution of the collaboration network. Section 5 analyzes the impact of social capital on innovative performance. Section 6 concludes.

2. Structural Composite Materials

60 Structural Composite Materials (SCM) were first developed by chemists in the early 20th century and have since been used in sport equipment and the automotive industry. It caught the attention of civil aircraft manufacturers during the late 70s. During this period, research programs focusing on the optimization of energy consumption were launched by the European Union
65 and the american government. The aim of these programs was to exploit composite materials in order to increase energy efficiency for aircrafts by the means of weight reduction. This makes SCM the perfect candidate for a study to analyze how a network is structured in order to absorb an existing technology from other sectors and develop it for its own needs.

70 The aerospace sector has a particular structure, it is organized as a production chain. An aircraft being a multi-technological product, each part of the airplane is developed in a different part of the network (see chapter 4 for more details).

In the value chain that makes up the sector, a small number of firms occupies
75 a strategic (central) position, these firms assemble intermediary products before sending them to either the final assembler (Airbus, Boeing etc.) or to other firms that use intermediary goods for larger parts. Firms with these specific positions in the value chain are called "pivot firms" (Frigant et al., 2006). These firms have to master all the technologies of the downstream
80 firms in order to complete their part of the aircraft.

The introduction of a new technology such as SCM, can only succeed if the value chain adapts to the technology. Indeed, the introduction of SCM alter the structure of an aircraft in many dimensions. Pivot firms have to adjust their production methods and hence so do the downstream firms. Integrating
85 SCM in the aerospace industry hence implies a thorough understanding of the core and linkage technologies (Prencipe, 1997) by all the actors implicated in aeronautical programs.

3. Data and methodology

In order to generate the collaboration network around the SCM technol-
90 ogy in aeronautics we need to identify all firms working with SCMs. We call this first step "Technology Framing".

3.1. Technology framing

We used patent and publication data to generate our network. Patents were extracted from Orbit while publications were extracted from Scopus.
95 In order to extract all relevant patents and publication we started by framing the technologies involved in the production of SCM. The framing process is an iterative process based on discussions with engineers and executives from the aerospace sector.

We conducted an initial search for relevant IPC codes by identifying parts
100 of the aircraft that can be made out of SCM. A detailed search was then conducted in order to identify what specific products and technologies are involved in the creation of composite materials (resins, matrices). We then discussed these codes and terms with engineers who would confirm or in- firm the relevance. New codes and terms were identified based upon these
105 discussions and then discussed again. This process allows us to frame the technology and build up a query that extracts patents beyond the scope of keywords which would result in false positives and unidentified patents and publications.

Two queries were constructed, one for publications and one for patents. The results in figure 1 show the evolution of the number of patents and publications identified. A total number of 9000 patents and 12000 publications were identified worldwide between 1980 and 2014.

The analysis was initiated in 1980 since it is the point at which SCM caught the attention of aircraft manufacturers. We checked patents and publication before 1980 and confirmed the latter.

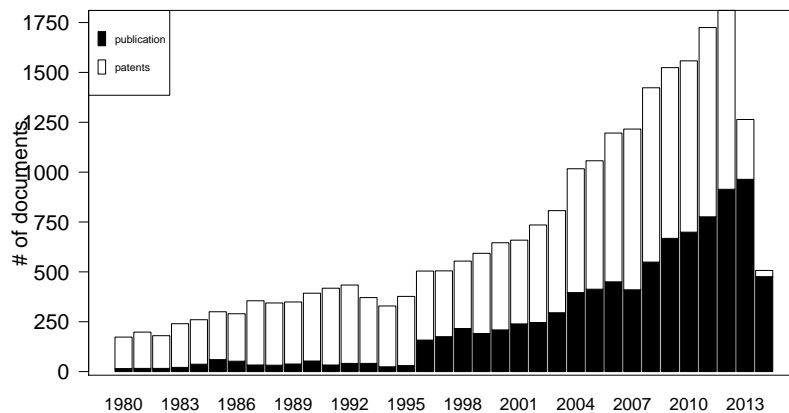


Figure 1: Distribution of the number of patents and publications over time.

3.2. Data treatment

The collaboration network. We used the previously described query to extract patents and publications.

The Orbit database uses algorithms to extract and translate data from patents, this results in terms that get lost in translation and textual mistakes. In addition to this, names on patents often do not match names on publication. For example, we observe the name "Airbus SA" on a patent, "Airbus S.A". on a publication, even mistakes like "Aerhjbuss" appear in the data. We used Intellixir to clean any mismatches or textual mistakes. Intellixir is a browser based tool for patent and publication analysis. It has a feature that automatically cleans the data. A final treatment was conducted by hand to clean

any remaining problems.

130 Once the data was cleaned all firm names were extracted from the patents
and publications to generate a network. A link was created between two firms
that co-wrote or co-deposited a patent. A link resulting from a publication
was hence treated as a link resulting from a patent. A date was added to
135 each link, which was the priority date for patents and the publication date
for publications.

From this data we create two series of temporal networks, a first using
a 5-year window Powell et al. (2005), Buchmann and Pyka (2013), a second
using a cumulative method. Each method adds specific information about
140 the evolution of the network. The 5-year window allows us to put an end
date on a collaboration. This method allows us to track the number of active
firms in the network and how they are connected, allowing us to track more
precisely when the network starts to decline. It paints a precise picture of the
behavior of firms and the interest they have for the technology. For example,
145 if the technology has become obsolete this will be visible by a decline in the
number of firms present in the network and an absence of new firms. From a
purely practical point of view it allows us to delete bankrupt firms, or firms
which changed their name from our dataset.

The cumulative network keeps the history of the network, this allows us to
150 observe if old firms work more intensively together or if the evolution is de-
fined by new entrants. It allows us to see where a particular technology
was fostered and how it spreads through the network (by bridging structural
holes for example).

For the purpose of knowledge collaborative behavior we will use the 5-year
155 window network. For the purpose of knowledge flows we will focus on the
cumulative network, even if the collaboration is over firms still have a social
link with each other and collaborations hence last longer than the time they
work together Dahl and Pedersen (2004).

Since this network shows the origins of technologies. Even if a collaboration
160 does not exist anymore, and the firms has exited the network, the knowledge
still exists and is still exploitable.

For the purpose of identifying knowledge (creation and flow) we use IPC
codes present on patents. For the specific analysis of the flow of knowledge
we will use patent citations to identify which firm is influenced by which firm.
165 This will allow us to track when a firm starts working on a specific technology

and who the firm learned from In addition, since we have dynamic data, it will allow us to see if some firms are leaders and other followers.

The knowledge network. In order to identify the life-cycle of the technology we use IPC codes present on the patents. Whenever two or more IPC codes are present on the same patent a link is created between them. The International Patent Classification (IPC) classifies patented technologies according to different technological fields. The system itself is crescendo in nature. The more digits, the more precise the codes become from a technological point of view. A 4-digit level defines a broad definition of technologies, for instance B64C defines "Aeroplanes; helicopters". The 7-digit level goes one step further into detail by specifying for B64C1, "Fuselages; Constructional features common to fuselages, wings, stabilizing surfaces, or the like". Going a step further, at the 9-digit level we will find "Floors" for code B65C1/18. We use 3 different digit levels for our analysis, the 4, 7 and 9 digit levels. In order to obtain a 4-digit network, all IPC codes are reduced to their 4-digit format. For example B64C001/23 is a 9-digit code, in order to obtain the corresponding 4-digit code, one simply reduced the code to 4-digits: B64C. The same goes for the 7-digit code which would be B64C001 in this example. Just as for the collaboration network we use a 5-year window and a cumulative method.

4. The technology life-cycle

In the early phases of the technology life-cycle patents are deposited using codes that refer to the core elements of the technology. This should result, as the number of patents increases, in the appearance of a cluster interconnecting all the core-technologies. This core is reinforced as the number of patents increases since the same technologies are used. From a structural point of view:

Hypothesis 1: We should hence observe an increase in the clustering coefficient of the network during this research phase.

Once the research phase has reached its peak the development stage starts. This stage is defined by the incorporation of the technology for new applications. These applications are less densely connected than the core technologies since they have specific applications. In the knowledge network

this means that new nodes are added to the previously build cluster. From a structural point of view

Hypothesis 2: this results in a decrease of the clustering coefficient since the nodes are added to the periphery of the network and will not interconnect with other IPC codes relative to other applications. The average distance (as well as the diameter of the network) should increase due to these new nodes.

In theory then,

hypothesis 3: the network should have the structure of a core-periphery network.

I will start by checking for the presence of a core-periphery structure before proceeding to the analysis of the evolution of the clustering coefficient and the average distance.

4.1. Core-periphery check

Checking for a scale-free structure is done by fitting a function to the cumulative degree distribution of a network. A CP network has a small number of highly connected nodes (the core) and a large number of (relatively) less connected nodes (the periphery). This can be observed directly when we represent the degree distribution of the network. Which is simply a plot with the number of nodes with degree k on the y-axis and the degree on the x-axis. This distribution is then transforms into a cumulative degree distribution as can be seen in figure 5. A function is fitted to the CFD in order to check for a core-periphery structure. The most sought-after (and found) structure is represented by a power law which has the form: $p(k) = c \cdot k^{-\alpha}$. In a log-log plot this non-linear function becomes linear. We also check for another form which is the log-normal function. The functions are fitted using a maximum likelihood estimation. As previously a 5-year window and a cumulative method are used.

Figure 7 shows the results for the 4-digit network. Even though the p.value for the window configuration shows that the power law fit is statistically significant, this is only the case for part of the distribution. Indeed we can see that the straight line starts towards the end of the distribution. We hence cannot confirm that the distribution follows a power law. However the log-linear distribution is both signification and represents almost the complete

distribution. This confirms the presence of a core-periphery structure at the 4-digit level. The log-linear form shows a small decrease in the fraction of nodes when the density is decreased by a factor of 1 at the beginning of the distribution. This remains the case until a density of 20 showing that the network is quite densely connected. Almost all nodes have at least 3 links. The core is much more densely connected than the scale-free network identified in chapter 4. The core is hence surrounded by a periphery that is itself (relatively) densely connected as shown in figure 7. We hence conclude that the 4-digit network has a core-periphery structure. Both in the 5-year window case and the cumulative method. The same conclusion is valid for the 7-digit network even though the window shows that the core-periphery structure appears towards the end of the period. The 9-digit network structure also has a core-periphery structure when we consider the cumulative method. The window method does not show proof of a core-periphery network. We deduce from these results that hypothesis 3 is verified. The P.values for all configurations are provided in the annex.

4.2. Clustering and average distance

Now that we have established that the structure of the network is indeed
255 a core-periphery structure. We now turn to the analysis of the structure of
the network.

Figure 8 shows that the clustering coefficient in the 4-digit configuration
is high from the start due to a relatively small number of nodes. In figure 8
we see that the number of technological combinations is exhausted towards
260 the end of the period (i.e the number of links stabilizes in the +1 method).
In addition this core is very densely connected (density =0.95) hence 95%
of all possible links are present. The clustering coefficient is decreasing over
the whole period in the additional configuration. Figure 2 shows the densely
connected core of the IPC network at the 4-digit level.

- 265 1. B29C: SHAPING OR JOINING OF PLASTICS; SHAPING OF SUB-
STANCES IN A PLASTIC STATE, IN GENERAL; AFTER-TREATMENT
OF THE SHAPED PRODUCTS
2. B32B: LAYERED PRODUCTS, i.e. PRODUCTS BUILT-UP OF STRATA
OF FLAT OR NON-FLAT, e.g. CELLULAR OR HONEYCOMB,
270 FORM
3. B64C: AEROPLANES; HELICOPTERS
4. B64D: EQUIPMENT FOR FITTING IN OR TO AIRCRAFT; FLY-
ING SUITS; PARACHUTES; ARRANGEMENTS OR MOUNTING
OF POWER PLANTS OR PROPULSION TRANSMISSIONS IN AIR-
275 CRAFT

The combination of these technologies make perfect sense since the tech-
nology under study is a combination of aircraft technologies and the devel-
opment of composite materials. Around this core we find C-section codes
relative to chemistry, G-section codes relative to physics and H, mechanical
280 engineering. The construction of the core is clear.

In the 5 year window case we also see this decline even though there is an
increase in the later stages. Since the last 2 years are defined by a decrease
in the number of deposits (due to patent deposit times) in the later period
clustering goes up. Even the newer patents still have the core IPC codes
285 present, the lower number of patents hence result in the same core but lower
number of peripheral technologies which results in an increase in clustering.
This can be seen in figures 3. The number of new nodes as well as the number
of links is sharply reduced in the last periods.

The 7 and 9-digit network reveal more interesting information. We can observe a clear increase in the clustering coefficient from the beginning of the period to 1993 for the 7-digit network and 1995 for the 9-digit network. These dates coincide with the point at which the collaboration network enters the small world zone. From that point on the clustering coefficient declines until it increases again for the same reason as we previously discussed for the 4-digit network.

The peak is observable both in the cumulative network and the 5-year window even though the window networks are more hectic. These points seem to confirm our hypothesis that there is a link between the evolution of the IPC network and the collaboration network. In order to further investigate that the evolution of both networks are ruled by an evolution from research stage to development stage, (March, 1991). If this is indeed the case we should observe some variation of a core-periphery structure.

4.3. Network structure and the technology life-cycle

A network can evolve in two dimensions, the number of links and the number of nodes. Figure 2 shows the evolution of different network indicators from the cumulative network and from the 5-year window network.

The growth rate of the number of nodes shows that new firms appeared in the network each year. This growth rate is however not homogenous. Two phases can be distinguished in the evolution of the network. A first phase spanning from 1980 to 1995, highlights a high volatility in the number of firms present in the network and in the other network indicators. This phase is the research phase in the life-cycle of the technology, during which firms identify relevant partners to collaborate with. The number of collaborations decreases over time. Collaborations rely on trust and mutual understanding Floréan and Tell (2004) which take time to emerge between partners Prencipe and Tell (2001). When no previous interaction has allowed for the emergence of trust, firm use referrals to identify reliable collaborators Hanakia et al. (2010). This results in the creation of strong ties between firms which cooperate multiple times Granovetter (1983) and reduces, over time, the number of cooperations between firms since they will have a tendency to collaborate with the same firms Hanaki et al. (2010).

The number of links in the 5 year window network shows indeed a large number of collaborations in this early stage in the evolution of the network. Remarkably the clustering coefficient stays high and stable over this period of time. Implying that the number of links increases faster than the number

of nodes and that firms work together in close clusters. This can be easily understood since an airplane is made up from a different parts that require different technologies Prencipe (1997), each technology is fostered in its own cluster.

330 If we look at the 5-year window we observe that the number of firms in the network starts a significant decline in 1995, accompanied by a significant decline in the number of new collaborations in the network. This marks the beginning of the development stage.

335 The technologies developed by different firms are now diffusing though the network to be integrated in intermediary and final products. The intermediary product are assembled by firms with a strategic position inside the production chain called pivot firm Talbot (2013). The downstream firms which researched the technology now exit the network while the pivot firms
340 develop the technology further. This results in the a stabilization of the network indicators in the cumulative network implying that firms are working with firms with which they have established strong links in the past.

The network ends with a low centrality and high clustering coefficient,
345 clearly showing that the network is build from interconnected clusters.

4.4. Typology of the network structure

The interest in the global structure of a network is motivated by questions related to the efficiency of a network in terms of knowledge diffusion. Research on innovation network has resulted in the identification of several
350 typologies, mainly small worlds Watts (1999), Gulati et al. (2012), Tomasello et al. (2013), Baum et al. (2003)), scale free networks Barabási and Albert (1999) and nested split graphs König et al. (2011).

Small worlds are of particular interest since theoretical models show that this structure is particularly efficient when it comes to the diffusion of information
355 though a network. A small world network is characterized by a low average distance and a high clustering. The clustering assures that firms have enough access to diverse and new knowledge to innovate. The low average distance ensure that the knowledge is quickly transferred to the rest of the network. Following Watts and Strogatz (1998), Baum et al. (2003) and Gulati et al.
360 (2012) we check the structure of our network for a small world structure.

Gulati's Gulati et al. (2012) method compares the structure of an empirical network to that of a random network. We compute the clustering (C) and average distance (L) of our network, we then approximate the clustering (Cr) and average distance (Lr) of a random graph with the same number of links and edges. The clustering and average distance of both graphs are then compared. The idea is that we want an empirical clustering coefficient higher than the clustering in the random graph. However we want an average distance approximatively identical. For a graph to be a small world we hence want:

$$\frac{C}{Cr} \gg 1 \quad \text{and} \quad \frac{L}{Lr} \approx 1 \quad (1)$$

Figure 10 shows the results for our network for each year. We observe that the network converges towards a small world structure which it reaches around 1997, at the beginning of the development phase where knowledge flow intensifies. The network keeps it small world structure for about 10 years. During these years knowledge diffusion takes place. The technologies developed by the downstream firms are diffused to the pivot firms which include them for further development.

The observed decline is the result of the technology reaching maturity, firm may from that point on have turned their attention to a new generation of composite materials which might be outside of the scope of our query.

Our results are hence different from those found by Gulati et al. Gulati et al. (2012) who observed a network that kept the small world property at each point in time. Our result is due the fact that we analyze a network for one specific technology. At the genesis of the network small clusters forms in which different parts of the technologies are developed. These clusters interconnect over time reducing the average distance between firms, resulting in the observed convergence towards the small world structure.

One could argue that the convergence is the result of the increase in the number of firms in the network, resulting in a higher average distance. Figure 11 shows indeed that each year new firms are added to the network, while the clustering coefficient shows a steady increase.

The indicators used here are adjusted for network size in order to compensate for network size. Additionally, new firms enter the network even when the network diverges from the small world property. The convergence is hence the result of the propensity of firms to interconnect rather than the addition of new firms.

5. Micro-meso analysis

We will now turn our attention to a specific part of the network. In the aerospace sector, two major competing actors are of interest: Airbus and Boeing. As we discussed before, these firms need to be able to learn all technologies related to SCM in order to include them into the production of the final product. Based on what we previously discussed we can imagine two diverging strategies in terms of knowledge absorption for these firms. Either they decide to cooperate with firms from other sectors that have experience in the field or they cooperate based on social capital, i.e they pick firms based on their whether or not they have previously cooperated. In this section we will show how these two strategies lead to different results in terms of innovate performance.

5.1. Network position

Boeing was present in the network since the 1980's while Airbus entered the market a couple of years later (this is why all graphs start in 1985). A first clue giving away the diverging strategies can be observed in Figure 5. When Boeing entered the market and until 1998, it has a clustering coefficient of 0. The clustering coefficient measures the number of collaborators of Boeing that work together. A clustering of 0 hence means that none of the collaborators of Boeing have worked together. At the complete opposite we find Airbus which entered with a clustering of 1. Where Boeing took the risk of collaborating with firms specialized in composite materials¹, Airbus chose to cooperate with a cluster of its historical partners. The strong links the firm has created in the aerospace sector have highly influenced its absorption strategy.

These observations are reinforced by the study of the citation network of both firms. Figure 7 shows the firms cited by Boeing and Airbus and the firms citing Boeing and Airbus. We observe here that the European company is largely influenced by the firms it has previously collaborated with while Boeing has a larger variety in its inspirations. At the center of this graph we find firms that inspired both firms. Above Airbus we find firms that inspired only Airbus, underneath Boeing we find firms that only inspired Boeing. The larger the arrow the higher the number of citations between two firms. We hence observe that Boeing has a large variety of inspirations with a low

¹We refer here to firms that have worked with composite materials in other sectors

frequency while Airbus tends to cite more frequently the same firms. These firms are often previous collaborators.

Theory on preferential attachment Barabási and Albert (1999) suggest that firms might motivate their decision to cooperate with a specific firms if they have previously worked together. Firms who know each other have the advantage of cooperating more efficiently because they know how the other operates.

Boeing ignored these benefits and chose to identify specialists, with the risk it would lose in efficiency during the cooperation because of a lack of social capital.

Towards the second phase of the evolution of the network we observe that both firms have very similar positions in terms of centrality. The betweenness centrality measures the relative position of a firm on all the paths connecting all other firms. This means that a high betweenness centrality is synonymous with a position through which many information flows may be captured. Figure 5 shows that both firms converge to a similar level of centrality as can be observed for the other indicators. This implies that both firms had an identical position for the absorbing of new technologies which is expected considering their position in their respective value chain.

The number of cooperations marks however a point of divergence. Airbus has accelerated the number of firms with which it collaborates from 1997 onwards. Boeing on the other hand has been much more conservative, ending with less than half the collaborations of Airbus.

We observe two different strategies resulting in nearly identical network positions. The resulting innovative performance is however not the same as we will show in the next subsection.

5.2. *The race for innovation*

By extracting IPC codes from Boeing and Airbus' patents we are able to track when firms deposit patents in specific IPCs that are at the core of SCMs technology. Two of these core IPCs are: B64C1 ("Fuselages, Wings, stabilizing surfaces, or the like"²) and B29C70 ("Shaping composites").

From the patents we create a network connecting IPC codes with Airbus and Boeing. If there is a link between Boeing and B64C1 that means that Boeing has deposited a patent using this code. The results are shown in figure 6,

²Titles given by WIPO in the international patent classification

465 the thicker the link between the IPC and the firm the more deposits using
the IPC were identified.

In the center of the graph we find IPC that were used by both firms, the
most relevant IPC codes are found here. From a dynamic perspective we
470 can observe when a firms first deposits a patent in one of those relevant IPC
codes. We hence created a dynamic network that allowed us to observe when
a firm deposits its fist patent in a certain technology.

This representations can show how far a head (or far behind) a firm is com-
pared to another. In our case we observed that Boeing deposited in the 2
475 IPC codes 10 years before Boeing did, showing clearly that Airbus has a
technological lag compared to Boeing.

This lag can be explained by the previously identified strategy of Airbus,
who decided to research the technology with historical partners. This deci-
sion was made even though the identified partners might not have been the
480 most specialized firms in the sector.

Boeing’s strategy however paid off, it positioned itself as gatekeeper be-
tween two sectors and it took the risk of collaborating with firms it has
no connection with. Their knowledge absorption strategy was hence more
485 efficient.

6. Conclusion and Discussion

This document has shown that the evolution of the collaboration network
for a specific technology is correlated with the life-cycle of the technology. In
the research stage of the technology, small clusters form in which different as-
490 pects of the technology are researched. Over time these clusters interconnect
resulting in a convergence towards a small world structure at which point
the development stage starts and the technologies start to diffuse.

On a micro level we showed that a firm using social capital to find its collab-
orators fell 10 years behind a competitor who chose to cooperate with firms
495 that had experience with the technology from another sector.

7. References

Ahuja, G., September 2000. Collaboration networks, structural holes: A lon-
gitudinal study. *Administrative Science Quaterly* 45, 425–455.

- Barabási, A.-L., Albert, R., 1999. Emergence of scaling in random networks.
500 science 286 (5439), 509–512.
- Baum, J. A., Shipilov, A. V., Rowley, T. J., 2003. Where do small worlds
come from? *Industrial and Corporate change* 12 (4), 697–725.
- Buchmann, T., Pyka, A., 2013. The evolution of innovation networks: The
case of a german automotive network. Tech. rep., FZID discussion papers.
- 505 Cowan, R., Jonard, N., 2007. Structural holes, innovation and the distri-
bution of ideas. *Journal of Economic Interaction and Coordination* 2 (2),
93–110.
- Dahl, M. S., Pedersen, C. Ø., 2004. Knowledge flows through informal con-
tacts in industrial clusters: myth or reality? *Research Policy* 33, 1673–
510 1686.
- Dosi, G., 2000. Innovation, organization and economic dynamics: selected
essays. Edward Elgar Publishing.
- Floréan, H., Tell, J., 2004. The emergent prerequisites of managerial learning
in small firm networks. *Leadership & Organizational development journal*
515 25 (3), 292–307.
- Frigant, V., Kechidi, M., Talbot, D., 2006. Les territoires de l’aéronautique:
Eads, entre mondialisation et ancrage.
- Granovetter, M., 1983. The strength of weak ties: A network theory revisited.
Sociological theory 1 (1), 201–233.
- 520 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.
- Hanaki, N., Nakajima, R., Ogura, Y., 2010. The dynamics of r&d network
in the it industry. *Research policy* 39 (3), 386–399.
- 525 Hanakia, N., Nakajimac, R., Ogurad, Y., 2010. The dynamics of r and d
network in the it industry. *Research Policy* (39), 386–399.
- Kogut, B., Zander, U., 1992. Knowledge of the firm, combinative capabilities,
and the replication of technology. *Organization science* 3 (3), 383–397.

- 530 König, M. D., Battiston, S., Napoletano, M., Schweitzer, F., 2011. Recombinant knowledge and the evolution of innovation networks. *Journal of Economic Behavior & Organization* 79 (3), 145–164.
- March, J. G., 1991. Exploration and exploitation in organizational learning. *Organization science* 2 (1), 71–87.
- 535 McEvily, B., Marcus, A., 2005. Embedded ties and the acquisition of competitive capabilities. *Strategic Management Journal* 26 (11), 1033–1055.
- paolo Saviotti, P., May 2007. On the dynamics of generation and utilisation of knowledge: The local character of knowledge. *Structural change and economic dynamics* 18, 387–408.
- 540 Pippel, G., 2013. The impact of r&d collaboration networks on the performance of firms: a meta-analysis of the evidence. *International Journal of Networking and Virtual Organisations* 12 (4), 352–373.
- Powell, W., White, D., Koput, K., Owen-Smith, J., 2005. Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences1. *American journal of sociology* 110 (4), 1132–1205.
- 545 Prencipe, A., 1997. Technological competencies and product’s evolutionary dynamics a case study from the aero-engine industry. *Research policy* 25 (8), 1261–1276.
- Prencipe, A., Tell, F., 2001. Inter-project learning: processes and outcomes of knowledge codification in project-based firms. *Research policy* 30 (9),
550 1373–1394.
- Talbot, D., 2013. Clusterisation et délocalisation. *Revue française de gestion* (5), 15–26.
- Tomasello, M. V., Napoletano, M., Garas, A., Schweitzer, F., 2013. The rise and fall of r&d networks. arXiv preprint arXiv:1304.3623.
- 555 Tsai, W., 2001. Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. *Academy of management journal* 44 (5), 996–1004.

- 560 ven der Valk, T., Chappin, M. M., Gijsbers, G. W., 2011. Evaluating innovation networks in emerging technologies. *Technological Forecasting and Social Change* 78, 25–39.
- Verspagen, B., Duysters, G., 2004. The small worlds of strategic technology alliances. *Technovation* 24 (7), 563–571.
- Watson, J., 2007. Modeling the relationship between networking and firm performance. *Journal of Business Venturing* 22 (6), 852–874.
- 565 Watts, D. J., 1999. Networks, dynamics, and the small-world phenomenon 1. *American Journal of sociology* 105 (2), 493–527.
- Watts, D. J., Strogatz, S. H., June 1998. Collective dynamics of 'small-world' networks. *Nature* 393 (4), 440–442.

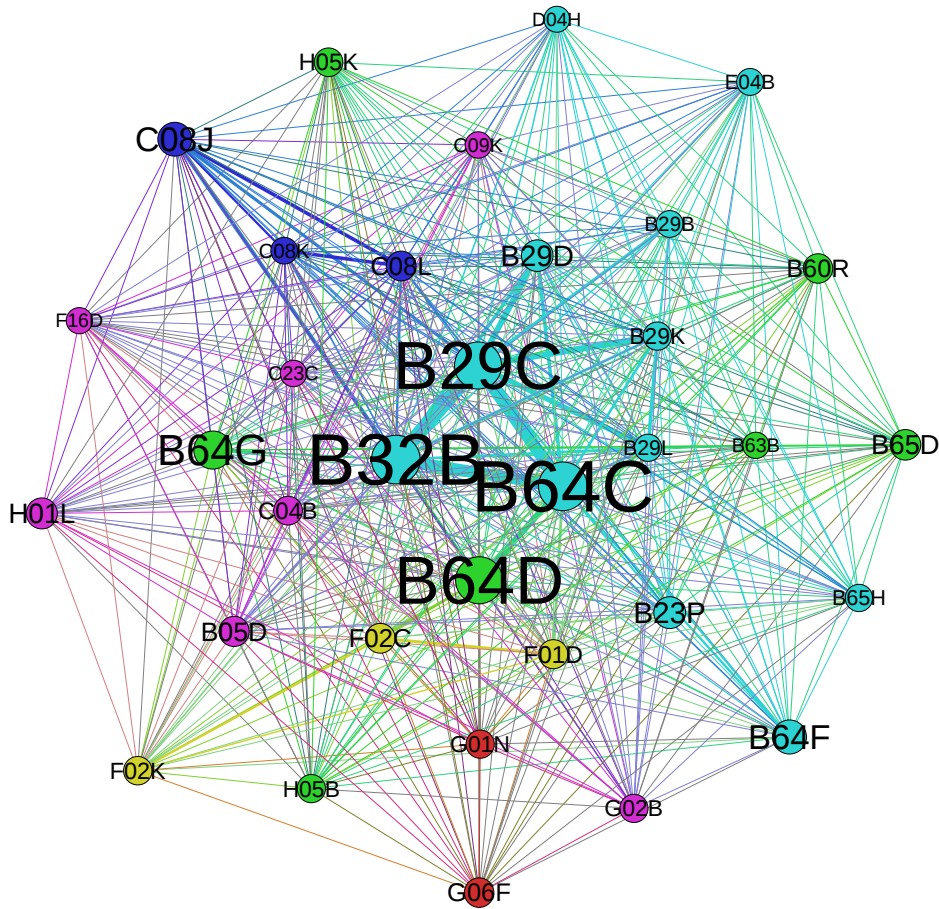


Figure 2: The technology core, representing a 95% interconnection rate

Figure 3: Evolution of the clustering coefficient in a 5-year window (left column) and a cumulative setting (right column) for the IPC network at the 4, 7 and 9 digit levels.

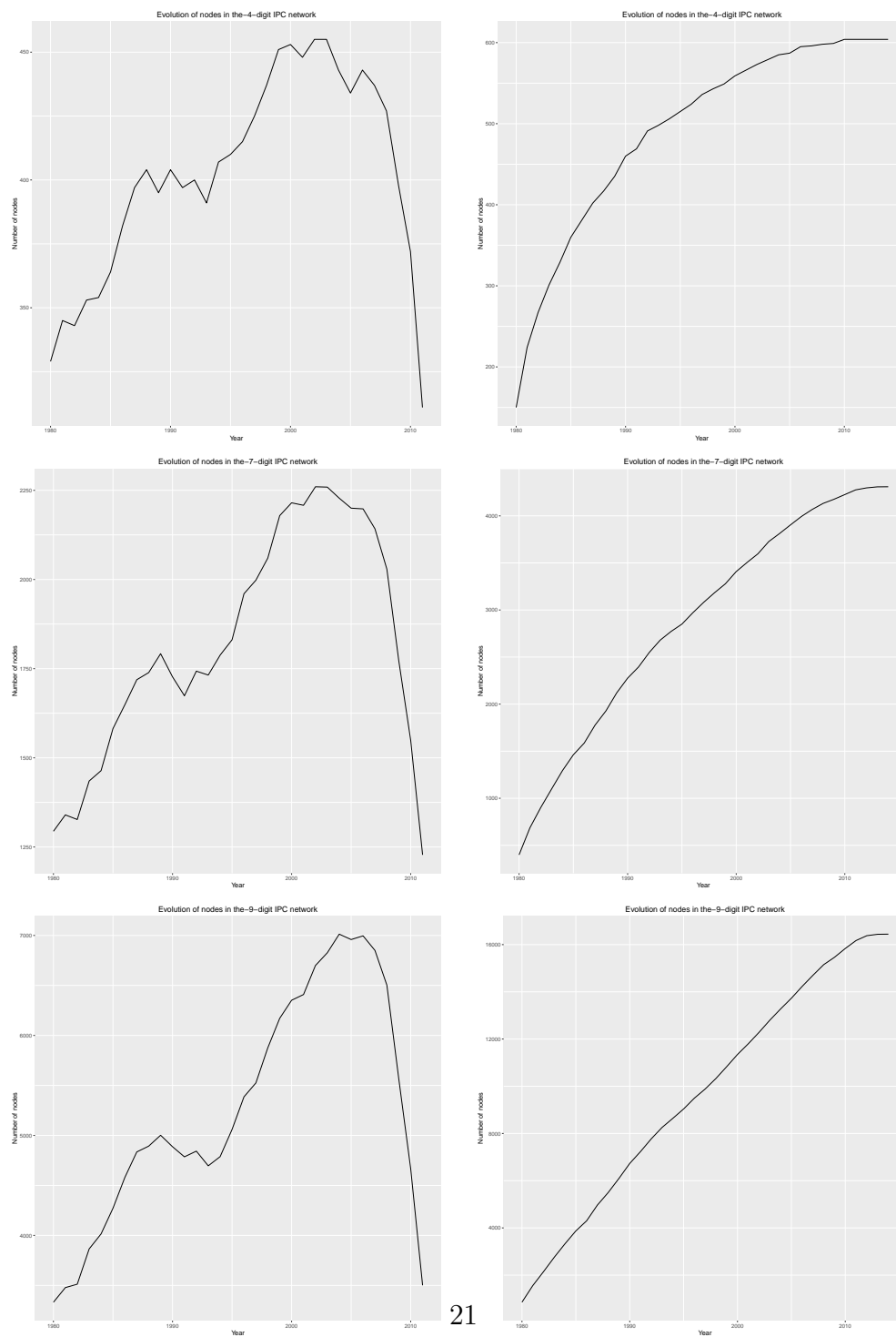


Figure 4: Power law fit to the IPC network at the 4 digit level. The cumulative method is on the left, the window method is on the right. A p.value higher or equal to 0.1 shows a good fit.

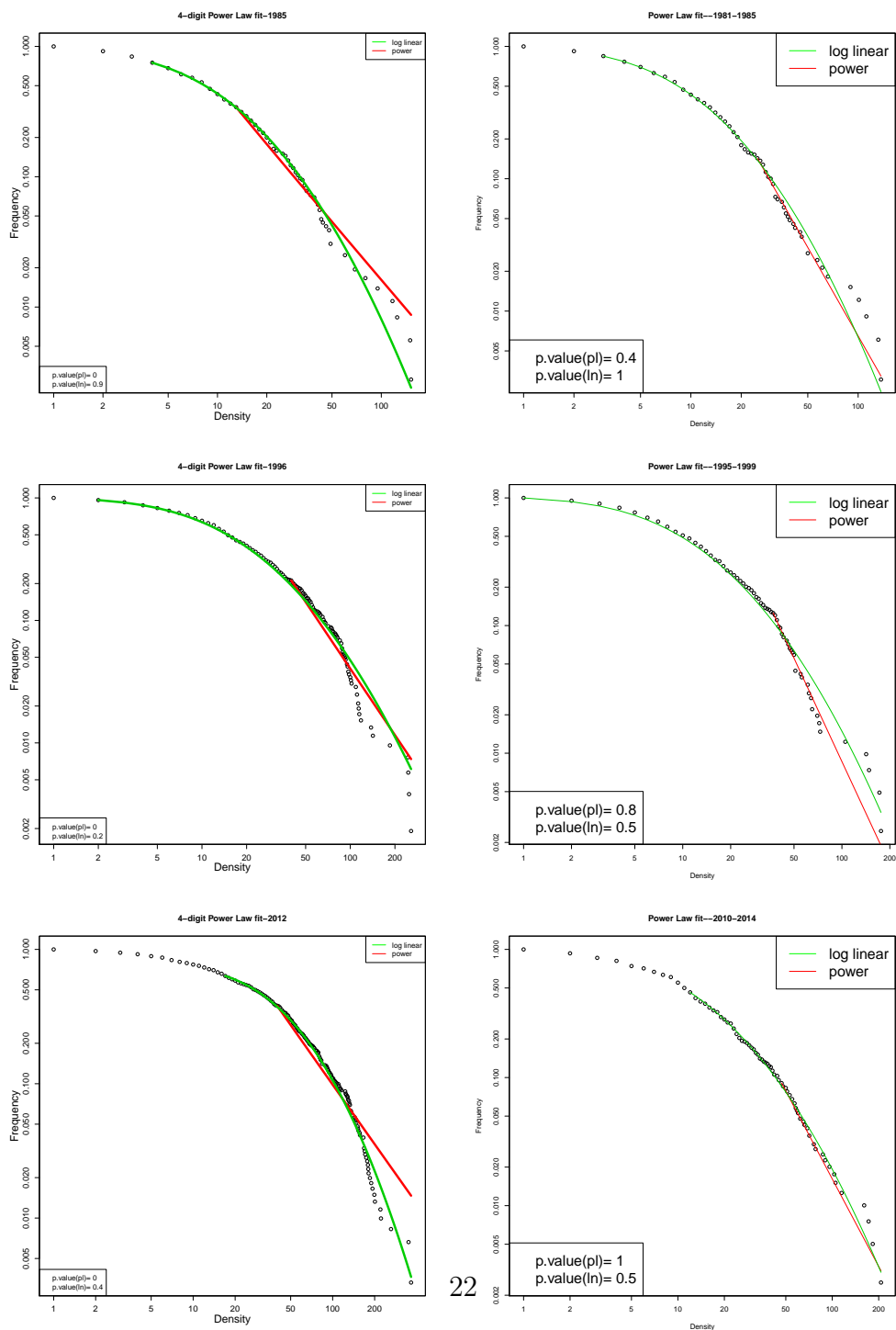


Figure 5: Power law fit to the IPC network at the 7 digit level. The cumulative method is on the left, the window method is on the right. A p.value higher or equal to 0.1 shows a good fit.

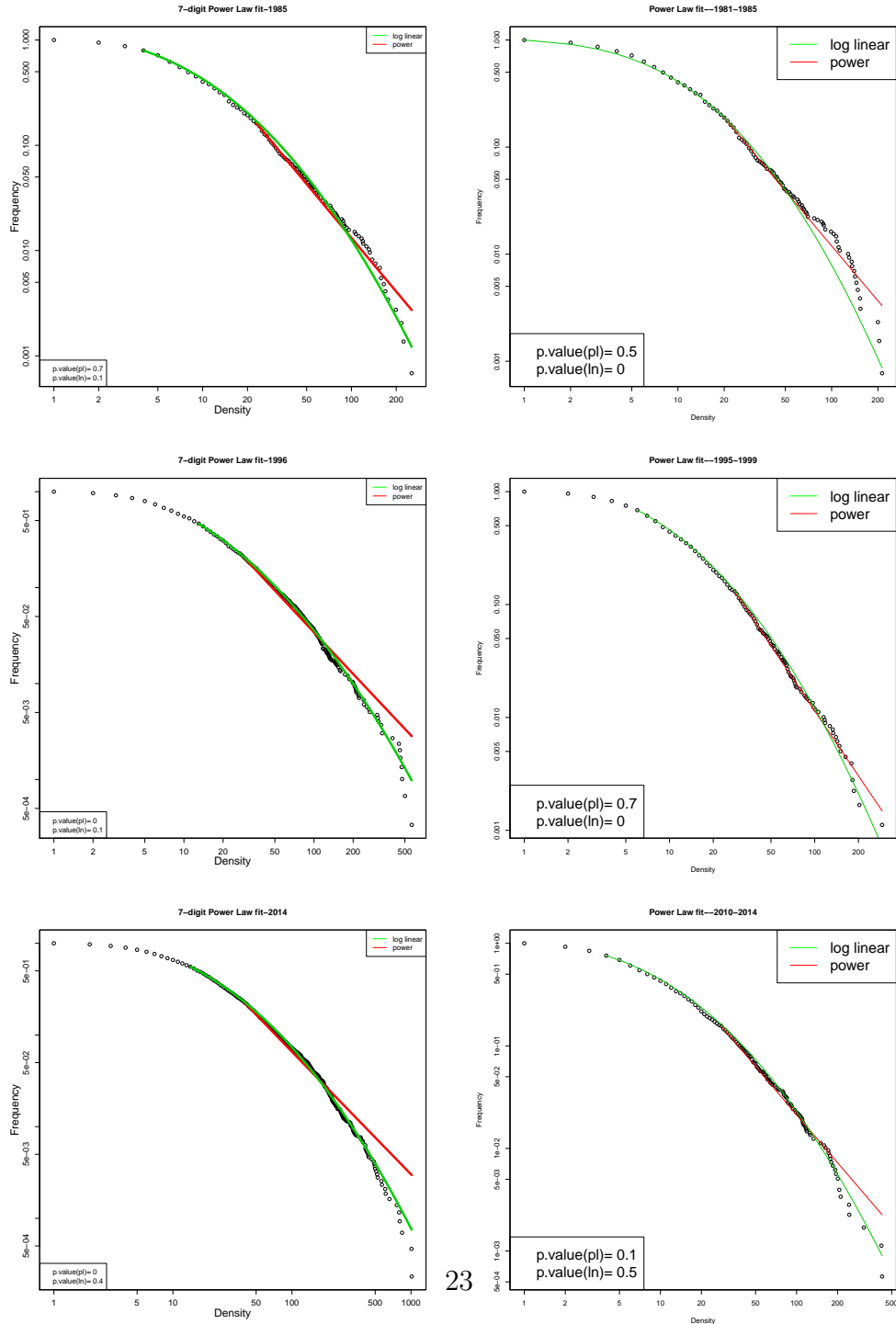
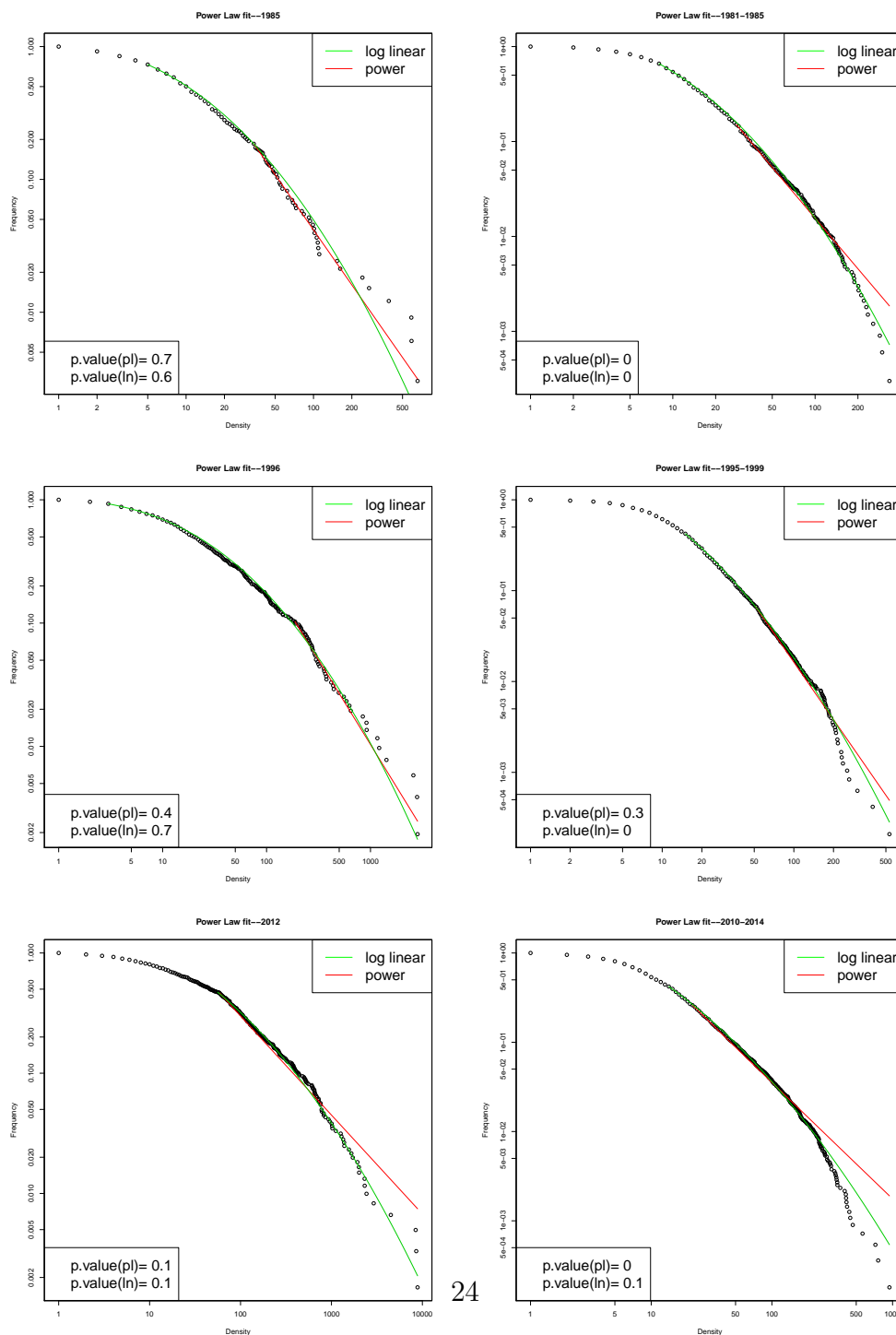


Figure 6: Power law fit to the IPC network at the 9 digit level. The cumulative method is on the left, the window method is on the right. A p.value higher or equal to 0.1 shows a good fit.



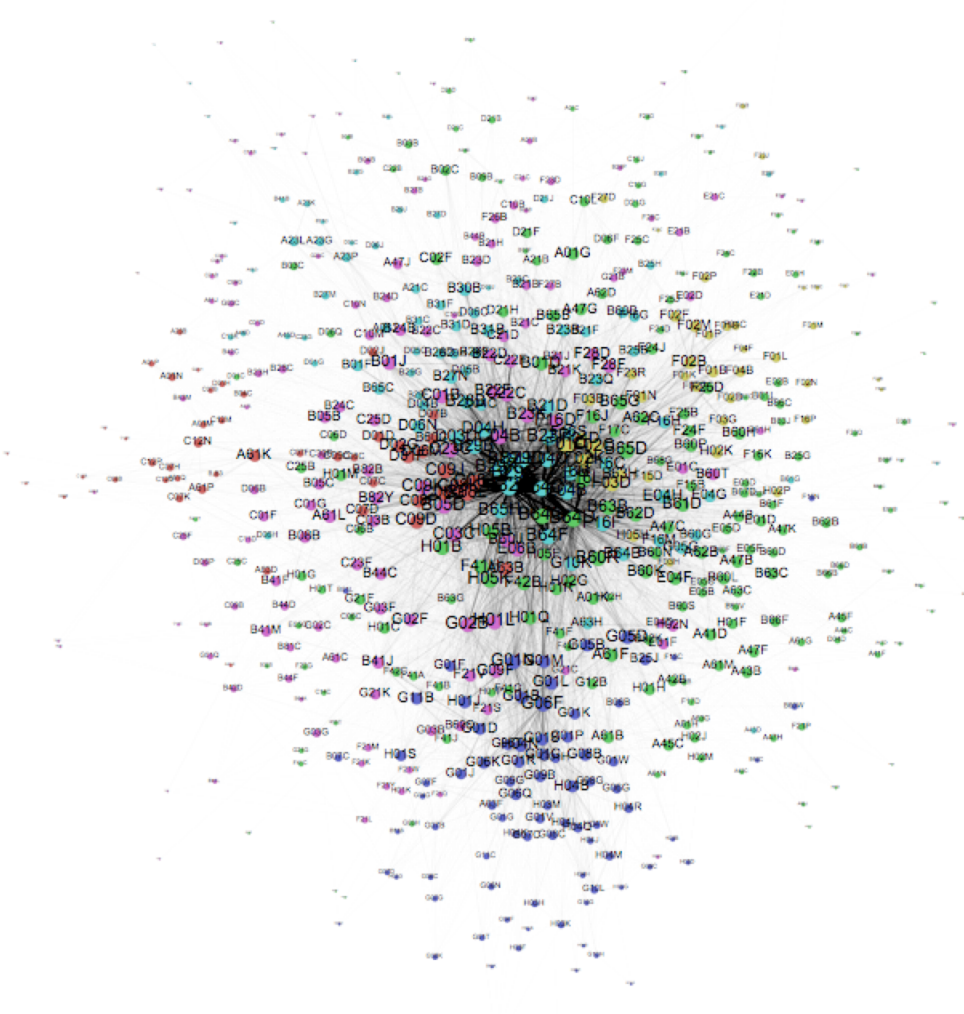
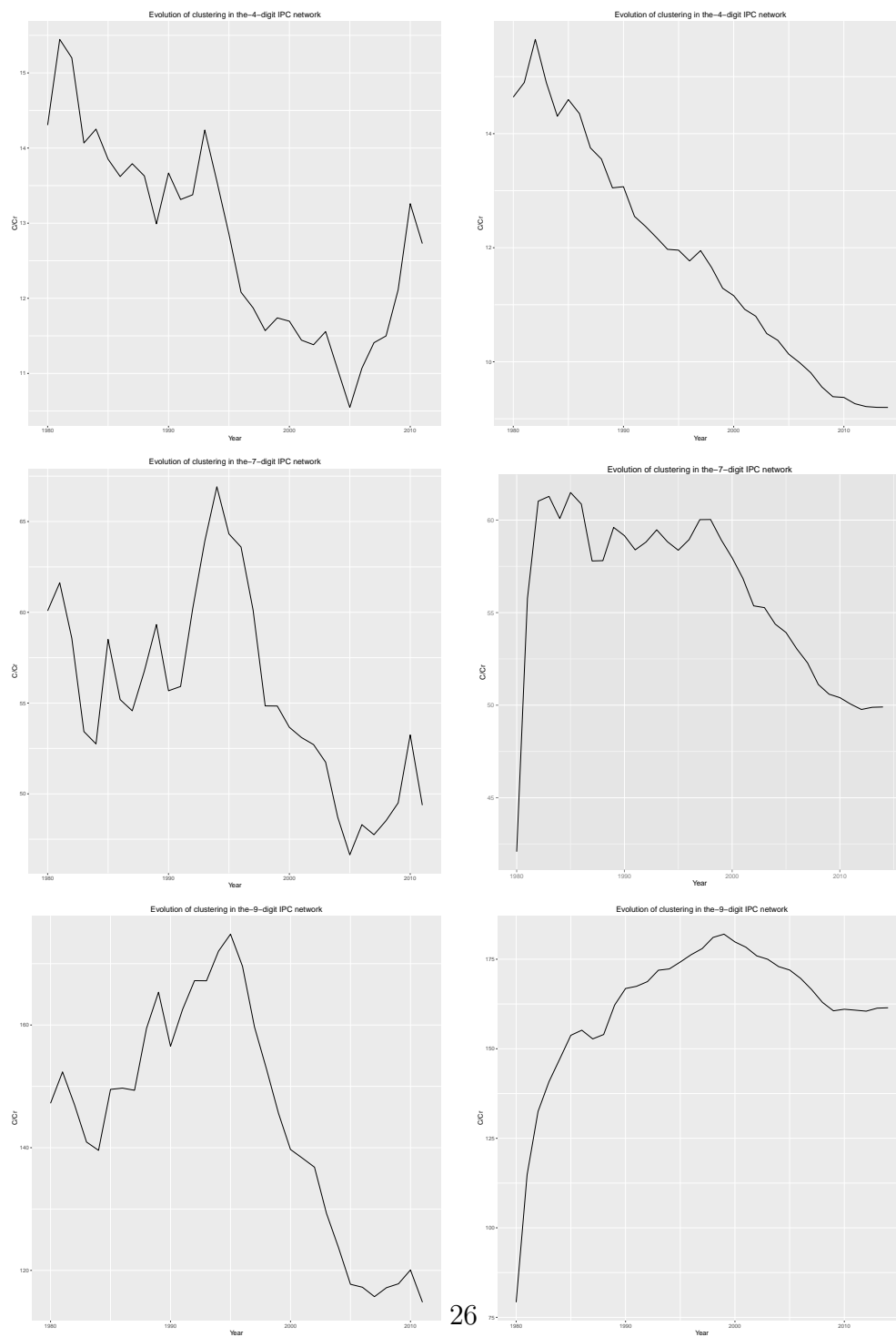


Figure 7: The full 4-digit IPC network for structural composite materials in aeronautics

Figure 8: Evolution of the clustering coefficient in a 5-year window (left column) and a cumulative setting (right column) for the IPC network at the 4, 7 and 9 digit levels.



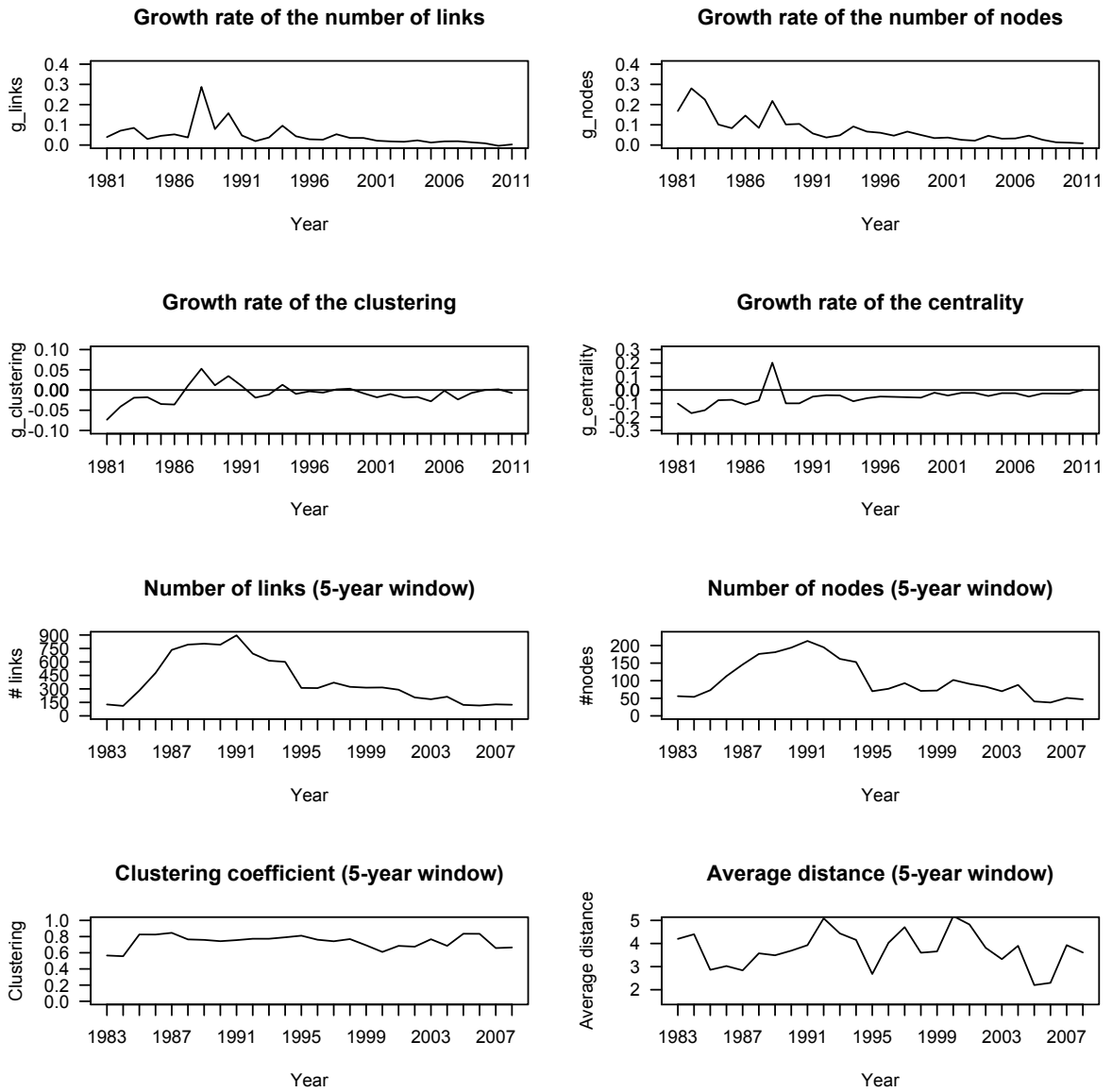


Figure 9: Evolution of network indicators

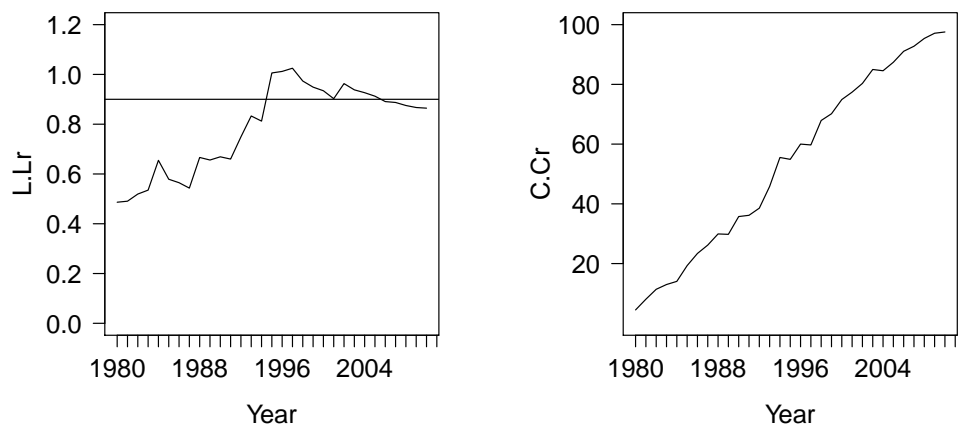


Figure 10: Evolution of small world ratios

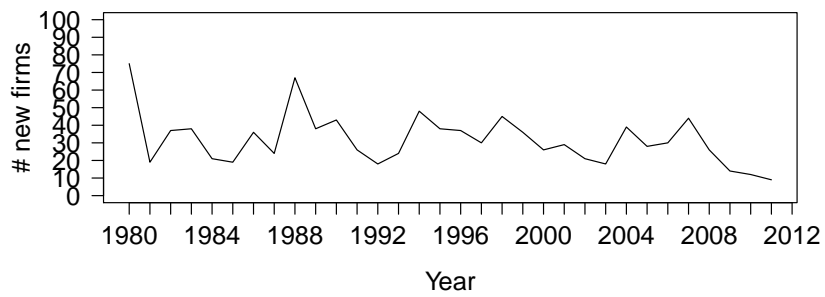


Figure 11: New firms in the network each year

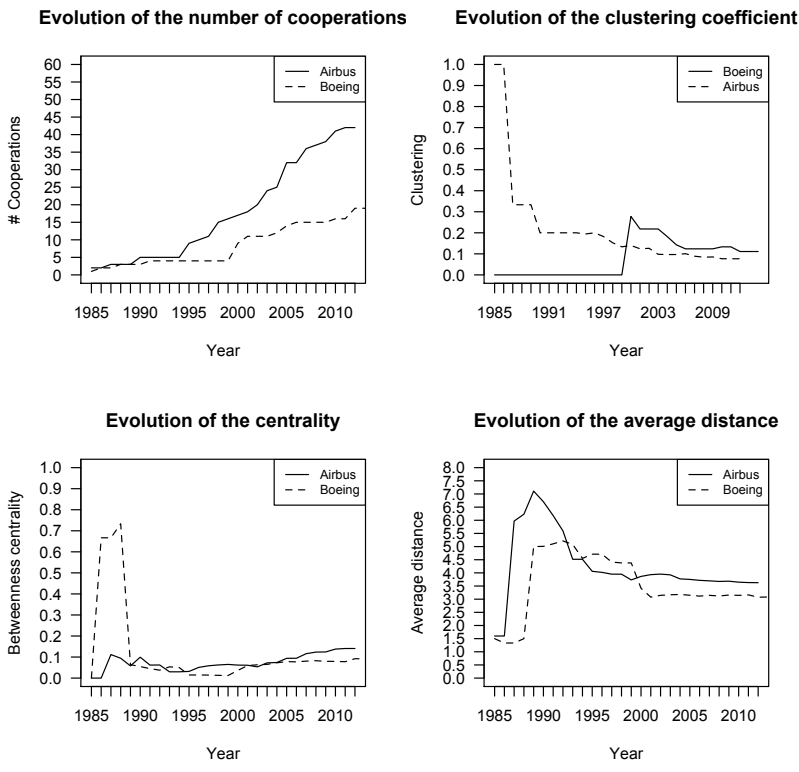


Figure 12: Evolution of the network position of Airbus and Boeing

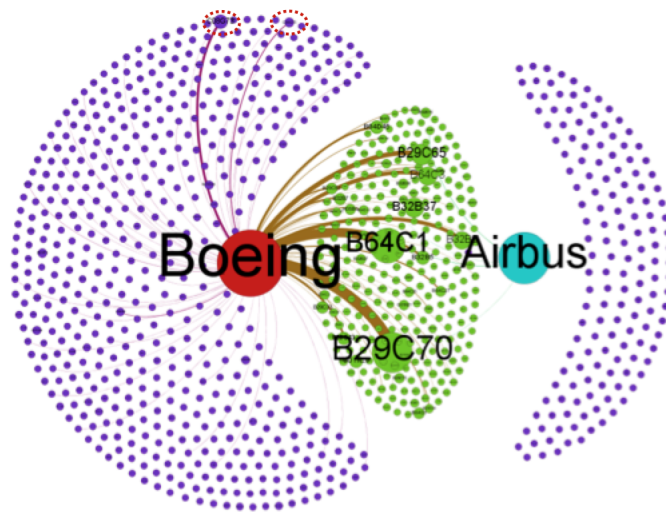


Figure 13: IPC network of Boeing and Airbus

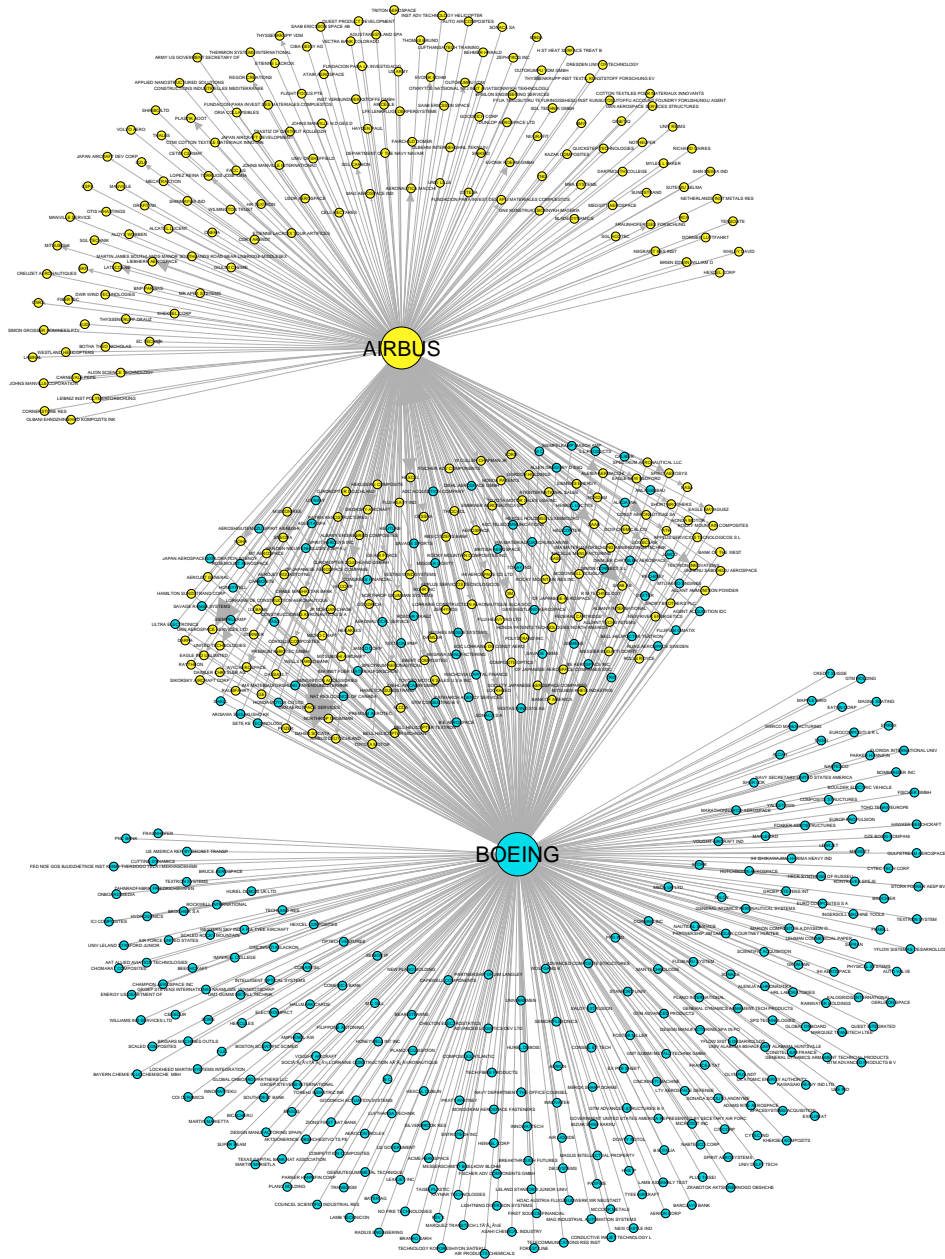


Figure 14: Citations of Airbus and Boeing