Do Network Dynamics Differ Between Technology Fields? Describing Complete Network Dynamics Using Network States and State Changes

Alexander Christiaan Smit
Vrije Universiteit Amsterdam
SBE / KIN Center for Digital Innovation
a.c.smit@vu.nl

Marius Meeus
Tilburg University
Organization Studies / Center for Innovation Research
m.t.h.meeus@uvt.nl

Jörg Raab
Tilburg University
Organization Studies / Center for Innovation Research
j.raab@uvt.nl

Abstract
Existing literature suggests a differentiated development of networks in different technology fields. However, innovation policy often displays a homogeneous approach towards structuring these networks and ensuring network viability. The question if interorganizational technology field networks differ in their development is therefore open for further exploration. By considering both network structural characteristics and the node set that comprises a network, we propose an analytical framework that revolves around the 'network state'-concept. We conceptualize this as a configuration of values in a five-dimensional state space: network centralization, network density, network size, the numbers of exiting nodes, and entrants? that captures all possible network states. This model of network states is used to explore the evolution of 7 distinct field networks of consortia over 23 years, using a latent profile analysis. This method allows a mapping of all possible dynamics of a network through tracing a sequence of state changes over time. Our findings reveal that network dynamics unfold over sequences of changes in five distinct states: formation, growth, stagnation, stability and disintegration. We find a core sequence of state changes of formation, via growth, to stability, but also find variations on and extensions of this pathway. The most important finding is that field network dynamics are anything but homogeneous. We find considerable differences in the duration of states across consortium networks in different technology fields. Based on the obtained insights, we formulate policy recommendations as a first step towards a more targeted and differentiated management of complete interorganizational technology networks.
Do Network Dynamics Differ Between Technology Fields? 
Describing Complete Network Dynamics Using Network States 
and State Changes

Introduction

The adage that in order to adapt to fast changing environments, generating innovation through networked collaboration is key (Birkinshaw, Bessant, & Delbridge, 2007; Powell, Koput, & Smith-Doerr, 1996) has resonated well with policy makers. Driven by the philosophy that stimulating joint research and development between research institutions and industrial organizations is one of the key drivers of economic growth (Aldrich & Sasaki, 1995; Branstetter & Sakakibara, 2002; Meeus, Oerlemans, & Kenis, 2008), governmental policies especially target the creation and consolidation of public-private links. Such policies aim, for example, at stimulating public-private mobility, public-private research consortia, and exchange and interaction between public and private organizations (Meeus et al., 2008; Peterman, Kourula, & Levitt, 2014; Salter & Martin, 2001).

In addition to the stimulation of collaboration between public and private organizations, a second key task for policy is to maintain network viability. One way of maintaining network viability is through sustaining the inflow of new nodes in a network. This impacts network viability in several ways, for example through adding diversity to existing network populations, enlarging partnering opportunities and signalling the value of new technological opportunities (Meeus et al., 2008). In addition to node entry, network size and nodes that exit a network can be considered as gauges for network viability: whereas size reflects the attractiveness of a technology network, node exits are an indicator of – amongst others – its level of competition. Gauging both viability features aids policy makers in avoiding bottlenecks, such as lock-in effects or the emergence of competitive barriers to collaboration and innovation (Rondé, 2001).

Government thus has an important role in the formation and subsequent dynamics of interorganizational networks geared towards technological development (Peterman et al.,
2014). However, an important issue that warrants further exploration of the dynamics of such networks is that, whereas current innovation policy assumes that field network dynamics are homogeneous (Meeus et al., 2008), other literature on industrial dynamics suggests that these field network dynamics are heterogeneous instead. Some sectors, for example, are shaped by high degrees of knowledge accumulation, whereas others can be characterized by a sustained level of knowledge diversification (Alkemade, Heimeriks, Schoen, Villard, & Laurens, 2015). Considering that a link has been suggested between the structural and dynamic properties of the firm population of a sector and its underlying technology field (van Dijk, 2000), we expect developmental differences between networks that form and develop in different technology fields.

If network development is heterogeneous across technology fields, this implies that policy measures should be tailored to the specific developmental features of such technology field networks. However, such tailoring of policy to the field network and technological dynamics is not without constraints. Some authors have criticized the idea that networks can be rationally steered, and pose that the processes that drive network formation and subsequent dynamics can be far less coherent, controllable and rational than contended (Doz, Olk, & Ring, 2000; Knights, Murray, & Willmott, 1993). This implies that policy has a limited role in early stages of network formation and development. Another group of scholars suggests that once networks have formed serendipitously, network members can become aware of one another and develop shared goals (Moretti & Zirpoli, 2016). The interdependencies that result from working towards these shared goals allow for more targeted policy interventions and coordination (Hite & Hesterly, 2001). This suggests that – depending on the pace and nature of network dynamics – there is a time for policy to let network development take its course, and a time to more actively steer this development. This timing, however, could be different for different technology fields. To what extent interorganizational technology networks differ in their development, however, remains a question that is open for further exploration. This paper
investigates this question and presents a method for describing the dynamics of such networks. This method in turn is applied to come to a comparison of seven distinct technology field networks.

To develop our model of state changes in field networks over time, we build on a research literature that explains causes and consequences, and typologies of organizational network development. First and foremost, this literature refers to the nodes that comprise a network, the ties that connect those nodes and the structure that results from these connections (Ahuja, Soda, & Zaheer, 2012, p. 435). Existing research on the topic of interorganizational network dynamics, seems to be biased towards drivers of tie formation between organizations as well as the dynamics of ties once they have been forged (Gulati & Gargiulo, 1999; Quintana-Garcia & Benavides-Velasco, 2004). Notwithstanding the importance and relevance of work that focuses on tie formation and dynamics, these studies do not offer a solid hold for describing and comparing the dynamics of interorganizational technology field networks, simply because they do not account for the set of nodes amongst which ties can be forged. The studies that look into the node dynamics and describe the development of such networks (e.g. Gay and Dousset (2005); Orsenigo, Pammolli, and Riccaboni (2001); Powell, White, Koput, and Owen-Smith (2005)), are limited in their generalizability, since they focus on one technological field (i.e. the life sciences field) only.

With this study, we research the development of interorganizational technology networks over time by focusing on understudied aspects of the definition of network dynamics by Ahuja et al. (2012). These reflect the earlier mentioned focus of innovation policy in the realm of networks and innovation: the structure of relations among organizations (i.e. network density and degree centralization), and the set of nodes – R&D consortia– that comprises a network (i.e. node entry, node exit and network size). These aspects are incorporated in a conceptual model that revolves around the heuristic of a network state. We explore this model using 7 distinct interorganizational technology networks in the Dutch context over a time span
of about 22 years. In these networks, nodes consist of R&D consortia, and the links between these nodes consist of joint membership ties. Using said parameters, we apply the technique of latent profile analysis to identify distinct network states. The outcomes of our analysis allow us to discern five distinct network states: formation, growth, stagnation, stability and disintegration. Although a common formation pathway lingers through the evolution of these 7 networks (i.e. from formation, via growth, to stability), we identify variations on and extensions of this pathway. In addition, we find considerable differences in the duration of states across networks.

This paper contributes to the existing literature on organizational networks and innovation in two related ways. First, organizational network scholars have been criticized to focus rather exclusively on network structure (Ghosh & Rosenkopf, 2015). By focusing not only on the development of network structure over time, but also by focusing on changes in the set of nodes that comprises a network, we add the population dimension to the study of network dynamics and combine this dimension with a network's structural development. Especially node entry and exit have been characterized already by Thorelli (1986) as key aspects that characterize network dynamics. The few studies on interorganizational network dynamics that included node turnover have offered interesting yet anecdotal insights with respect to the different roles played in a network by new entrants, incumbents and organizations leaving the network (Gay & Dousset, 2005; Orsenigo et al., 2001; Powell et al., 2005). By establishing a clearer link between node turnover and technology dynamics, we make its role in network dynamics more explicit.

Second, despite many calls for research on interorganizational network dynamics (Brass, Galaskiewicz, & Greve, 2004; Gulati, 1998; Parkhe, Wasserman, & Ralston, 2006), research on the topic has not thrived. Indeed, at first sight our research question (do technology networks differ in their development?) seems rather trivial. This simplicity is intentional, as answering this question turns out to be far from simple: many authors have pointed at the
inherent difficulties involved in collecting datasets for the longitudinal analysis of complete networks. This is the main reason for the slow progress of research on the topic of network dynamics (Cattani & Ferriani, 2008; Provan, Fish, & Sydow, 2007; Tsai, 2000). Not only does this result in network dynamics studies considering only limited time frames, it also means that, to the best of our knowledge, none of these studies has investigated more than one technology field. This renders a comparison across networks in different technology fields and hence differentiation of innovation policy based on technology fields impossible. Using a dataset that tracks the network development of 7 distinct field networks over a longer period allows us to describe and compare technology field network dynamics in this study. Consequently, we offer insights in network dynamics across a broad array of different field networks, as well as over many years within each of these networks.

Our research also yields useful insights for those involved in innovation policy. The networks studied in this paper emerge because of a governmental funding system. Given the importance of networks for both organizational and network-level outcomes, there is an important governmental stake in setting up policies in such a way that these networks are steered towards modes of organization that make them as effective as possible. In this light, getting insight in the predictability with which such networks develop over time and the duration of different developmental stages is fruitful and necessary in order to develop a more targeted and differentiated approach towards steering such networks (Dagnino, Levanti, & Mocciaro Li Destri, 2016; Provan et al., 2007). Hence, our study marks a first step towards the more targeted management of these networks, by providing insights in their developmental patterns and parameters that drive these patterns.

**Theoretical framework**

In this paper we develop a framework that can be used for describing network dynamics and specify the parameters that will be considered. Consequently, by applying this framework to different networks, a comparison between these networks can be made. We build forth on the
work on network dynamics by Ahuja et al. (2012) and the industry dynamics literature in developing this framework: both will be shortly described first, and then the phenomenon the framework describes, network dynamics, is linked to technology dynamics.

Ahuja et al. (2012) propose that the dynamics of any network can be conceptualized in terms of change in the nodes that comprise the network and change in the structure that results from the ties that connect those nodes (Ahuja et al., 2012, p. 435). Both aspects are included in our conceptual model in Figure 1. Central to this model is the heuristic of a network state. This state includes both the dimension of network structural features (i.e. network density and degree centralization) and the dimension of features related to the set of nodes that comprise the network (i.e. size, node entry and node exit). Network states are bounded by a state space, which is the space of all possible states of a network. Hence, all possible state sequences of a network will trace a path in this state space (Bickhard & Campbell, 2003; Kauffman & Oliva, 1994).

**FIGURE 1**

*Conceptual model depicting network state features and the state space*

Whereas different conceptual approaches towards explaining network formation and development exist (e.g. Doz et al., 2000; Ring & van de Ven, 1994), we apply an empirical approach to discern distinct developmental phases. Movement of a network through the state
space is determined by initial conditions of the network itself, as well as various constraints on
dynamics operating in the state space (Bickhard & Campbell, 2003; Makadok & Walker, 2007).
As our focus is on describing the dynamics of technology networks, we propose these
constraints are posed mainly by the technology field in which nodes in a network operate.

**Technology dynamics and network dynamics**

Existing literature suggests that the dynamics of interorganizational innovation networks and
technological development are closely intertwined. Various innovation scholars have
elaborated on the importance of interaction for the process of innovation (Lundvall, 1992;
Pavitt, 1984; von Hippel, 1988). Indeed, many scholars have described the joint development
of networks with a variety of technologies and bodies of knowledge (e.g. Gay & Dousset, 2005;
Gilsing, Cloodt, & Roijakkers, 2016; Orsenigo et al., 2001; Powell et al., 2005). Hence,
interorganizational R&D networks form around technologies, and the dynamics of such
networks consequently are linked to the development of these technologies.

Technological development can be conceptualized as a search process by network nodes
in a technology landscape (Aharonson & Schilling, 2016). We add a dynamic perspective to
this heuristic: the technological development that results from search in a technology landscape
subsequently changes that landscape. New search directions might emerge and become more
dominant. This makes existing search directions less salient or even obsolete. Before we can
explore how this change in the technology landscape affects the selected network dynamics
parameters, we need to delve deeper into the nature of technological development and the link
between technological development and network dynamics.

With respect to the nature of technological development, such development can be
characterized in terms of technological paradigms and technological trajectories (Dosi, 1982).
A technological paradigm embodies heuristics with respect to aspects and functions of a
technology that should be the object of search, and aspects and functions of that technology that
should be left unchanged or sacrificed. This includes the extent to which technological opportunities are present, the level of innovation cumulativeness, and the extent to which knowledge is codified (Safarzyńska, Frenken, & van den Bergh, 2012). With that, it reduces the relevant design space, and guides search in the remaining design dimensions (Frenken, 2006). The cumulative series of innovations within a technological paradigm create a technological trajectory. Along such a trajectory, dominant designs are incrementally improved to raise performance in certain functional attributes. Hence, technological development can be conceived as the progress along a technological trajectory that is defined by a technological paradigm (Dosi, 1982).

Inherent to this characterization of technological development is that this development has a natural tendency to converge to a dominant design. Technological breakthroughs, however, make that existing trajectories ultimately run into decreasing returns (Anderson & Tushman, 1990; Drazin & Schoonhoven, 1996). Scholars have generally acknowledged that after such technological breakthroughs a period of technological ferment takes place. During this period, different designs compete with one another. What follows is a maturation stage, where selection among competing designs often leads to convergence on one dominant design that can be further elaborated on (Agarwal, Sarkar, & Echambadi, 2002; Anderson & Tushman, 1990; Grodal, Gotsopoulos, & Suarez, 2014; Schumpeter, 1934; Tushman & Anderson, 1986). Hence, for some time it is not clear which technological aspects and functions are viable for further development, and it is unclear which directions in the search space are viable to pursue. Once a new dominant design is established, future discontinuities start a new cycle from breakthrough, via ferment and maturation to dominant design (Ehrnberg, 1995).

When considering the link between technological development and network dynamics, it must be recognized that often the described developmental cycle focuses on single technologies such as cars (Abernathy & Utterback, 1978), aircrafts (Frenken, 2006), or electronical components (James Wade, 1995). Yet, the literature suggests a role of
technological development in network dynamics as well (Capone, Malerba, & Orsenigo, 2013). At this level, however, the focus is on clusters of rather than single technologies (Castellacci, 2008; Teece, 2008). Hence, network dynamics are an aggregate reflection of the developmental cycles of all technologies that are developed in a network. How this is reflected in networks is an empirical question, yet this link will be tentatively explored for each of the selected network dynamics parameters in the remainder of this paper.

**Network size.** This dimension refers to the number of nodes that comprise a network (Ahuja et al., 2012). Network size in general reflects the attractiveness of a technology field (Afuah, 2013; Rosenkopf & Schilling, 2007; Suarez, 2005). This attractiveness is determined by, for example, the amount of resources available in a network (Brass et al., 2004; Meeus et al., 2008; Salavisa, Sousa, & Fontes, 2012), and available technological opportunities (Capaldo, 2007; Rodan & Galunic, 2004; Tang, Mu, & Maclachlan, 2008).

In the phase of established dominant designs, we expect network size in this situation to be stable over time (Malerba, 2002): the relevant design space of each technology is known, as well as the remaining search directions. Incumbent nodes will build forth on established dominant designs and the relative certainty in this situation can be expected to fill each possible position in the search space by incumbents. Uncertainty induced by a technological breakthrough, however, might lead to a change in size and a period of size fluctuation because a period of technological ferment and subsequent maturation begins. This fluctuation comes with node entry and exit dynamics.

**Node entry.** Node entry (i.e. the number of new nodes that enter a network) is considered an important aspect in the generation of network dynamics (Hakansson, 1992; Mowery, 1988). In a technology field in which mainly dominant designs are further improved, low levels of node entry can be expected (Kogut, Walker, & Kim, 1995; Kulve & Smit, 2003; Orsenigo et al., 2001; Owen-Smith, Riccaboni, Pammolli, & Powell, 2002; Powell et al., 2005). Under this
condition, node entry is discouraged due to the presence of high entry barriers, for example steep learning curves and economies of scale due to standardization (Agarwal et al., 2002; Malerba, 2002). Yet, some level of node entry can be expected, either through coordination of incumbents that search for co-specialization when further developing their established dominant designs (Lévesque, Minniti, & Shepherd, 2013; Orsenigo et al., 2001), or because some level of incumbent inertia that is inevitable as time progresses creates opportunities for node entry (Agarwal et al., 2002; Dercole, Dieckmann, Obersteiner, & Rinaldi, 2008).

Node entry levels change in the face of a technological discontinuity. In the event this discontinuity leads to a new technology field, new entrants behave like first movers in the initial stages of technological development. When successful as carriers of the field, these entrants later attract others as time progresses (Owen-Smith et al., 2002). Later entrants, however, can become technology field carriers as well. A common pattern when a disruptive technology is introduced in an existing technology field is that incumbent nodes react slowly with the result that leadership passes to pioneering new nodes that have embraced the new technology (Dosi, Faillo, & Marengo, 2008; Gay & Dousset, 2005; Malerba, 2002; Orsenigo et al., 2001; J. Wade, 1996) and challenge the existing paradigm (Gilsing et al., 2016; Kash & Rycoft, 2000; Lin, Chen, Sher, & Mei, 2010; Rosenkopf & Tushman, 1998). These later entrants do not necessarily have to be pioneers: some authors have suggested that incumbents from other technology fields can overtake an emerging one (e.g. chemistry-based pharmaceutical companies that enter the field of biotechnology (Roijakkers & Hagedoorn, 2006) with the aim of technological integration (M’Chirgui, 2009). Hence, node entry levels increase after a technological discontinuity as it opens new search directions in the technology landscape. The subsequent period of technological ferment still offers opportunities as well, which means that node entry level remains high (Agarwal et al., 2002). As technological development progresses further to the state of maturation and new dominant designs, we expect node entry levels to dampen.
Node exit. In comparison with node entry, research pays less explicit attention to node exit from networks in relation to technology dynamics, although it is reported by several studies (Gay & Dousset, 2005; Orsenigo et al., 2001; Owen-Smith et al., 2002; Powell et al., 2005). In networks in which mainly dominant designs are developed, node exit is associated with increased competition resulting from technological crowding and specialisation (Lin et al., 2010; Powell et al., 2005; Stuart, 1998), failure (Casper, 2007; Ingram & Torfason, 2010) or mergers (Powell et al., 2005): despite the presence of dominant designs, no best search direction can be determined a priori and therefore the creation of new applicable artefacts is far from a sure outcome of R&D (Drejer & Jørgensen, 2005; Hung & Tu, 2014; Nelson & Winter, 1982). However, we expect the level of node exit in this situation to be relatively low.

We expect node exit to follow the same pattern as that of node entry when a technological discontinuity with its subsequent stage of ferment occurs. Incumbent nodes might drop out of the network if they do not adjust or cannot contribute on time to the new technology (Dosi et al., 2008; Malerba & Orsenigo, 1999; Powell et al., 2005). In the subsequent stage of technological ferment, nodes that leave a network are the result of selection processes in the underlying technology field: better alternatives are selected and poorer ones are rejected (Baum & McKelvey, 1999; Mohrman, Gailbrath, & Monge, 2006). Node exit levels dampen as technological development progresses further to the state of maturation and a new dominant design.

Network density. This aspect denotes the cohesion of the relational structure in a network. As such, it cements nodes in a network and involves mutual awareness between network members of what others are doing. This facilitates mutual understanding and insight in knowledge interdependencies (Erikson & Bearman, 2006; Fagerberg, Fosaas, & Sapprasert, 2012; Fagerberg & Verspagen, 2009; Hollenstein, 2003; Koza & Lewin, 1999; Oh & Jeon, 2007).
Network density relates to technology field development in the following way. Under conditions of incremental improvement, preservation of a relatively dense network can be expected, as the fruitfulness of research directions and with that insight in knowledge interdependencies is clear (Gay & Dousset, 2005). In situations of technological discontinuities and ferment, however, we expect density to drop. In such situations, existing paradigms are overthrown. As we have seen, this results in higher attrition of incumbents from the field network, and the attraction of new entrants to the network. Together with this shift in direction of technological development, old relations disappear and new relations form (Mohrman et al., 2006), yet the uncertainty regarding fruitful directions hampers mutual awareness in the network.

**Network degree centralization.** Degree centralization refers to the extent to which one or few nodes in the network are more central compared to other nodes in that network. This indicates the presence of a small amount key players in the network that introduce common thematic foci (Fagerberg et al., 2012) and undertake continuous efforts to integrate the knowledge available in the network (Ata & Van Mieghem, 2009; Burt, 2007; Fagerberg et al., 2012; Fagerberg & Verspagen, 2009), in turn enhancing the collective perception of network members of viable technological alternatives and possible future developments, and focusing their commitment to a limited amount of core technologies (Afuah, 2013; Gay & Dousset, 2005; Soh, 2010) developed by central players (Gay & Dousset, 2005; Powell et al., 2005).

Under conditions of incremental technological change, technological development is in the hands of few incumbents. The literature suggests persistence in innovative activities by such nodes once roles are established (Cefis & Orsenigo, 2001; Triguero & Córcoles, 2013) and we therefore expect network centralization to remain stable over time in conditions of stability. In a situation of technological discontinuity and ferment, existing paradigms are overthrown. This results in a disruption of the network structure, as node turnover is likely to increase. The
resulting uncertainty and the associated loss of key players will temporarily lead to lower levels of network centralization.

The dimensions of state change model seem to be loosely associated with technological developments and therefore we propose that for rather distinct technological fields we expect distinct and therefore heterogeneous field network dynamics. This is our main proposition for this paper.

Data and methods

Research setting and data

The data that is used to study network dynamics in this paper is drawn from a dataset that was developed in the context of a larger overarching research project. This dataset was built using evaluation reports that in total cover 1,928 Dutch R&D consortia, funded by a Dutch technology foundation. The aim of this foundation is to realize knowledge transfer between the technical sciences and industry. In each consortium, an academic researcher designs a research and development project, and gathers one or more industrial organizations that see potential application value of the research results. Committed organizations are part of the ‘users committee’ that takes part in the research as from its early stages. Not only do these organizations discuss research progress and results in the light of potential application, they also contribute in kind and act as a testing-ground for the technology that is developed. A tie between two consortia is constituted by joint membership of one of the participating organizations or consortium leader in two consortia in the same year.

The first consortia started in the spring of 1981, and the most recent starting year that is included in the dataset is the year 2004. Because of joint membership in multiple consortia by both consortium leaders as industrial organizations, consortia are linked to one another. Following this approach, seven technology field networks were constructed, each on a yearly basis. Of the 1,928 consortia in the dataset, 153 consortia did not have any member reported.
In addition, 141 consortia were present as an isolate in one or more networks, and 40 were present as a dyad. These consortia were all excluded from the dataset, resulting in a total of 1,594 consortia spread across 7 technology fields. Depending on the year in which a consortium network emerged for the first time, the number of observations for each network ranges from 21 to 23 years, resulting in a total of 156 technology field networks. The consortium networks that emerge as a result can be considered a reflection of the organization of knowledge flows in the larger innovation system. Hence, investigating this organization is especially important for a targeted specification of innovation policy measures.

**Measurements**

*Network size.* This variable is expressed as the number of consortia in a network. We did not consider nodes that were isolated in the network, or part of a dyadic structure that was not connected to one of the network components.

*Node entry.* Taking \( t \) as the reference year, node entry is determined as the number of new consortia that entered the network at \( t \). A consortium was considered “new” when its leader was not involved in any other consortium three years preceding \( t \). Node entry was expressed as a count variable.

*Node exit.* Taking \( t \) as the reference year, node exit from a network was determined as the number of consortia that left the consortium network just before the network was observed at \( t \). Following the same reasoning as with node entry, a consortium was considered to exit the network when its leader did not appear again in the three years after \( t \). Node exit, too, was expressed as a count variable.

*Network density.* Cohesion through inter-consortium ties was captured in the measure of network density. This measure was calculated for all 156 networks by dividing the actual number of ties present in each network by the total number of theoretically possible ties in that network, taking into account that the joint member ties in the consortium network considered
are undirected (Scott, 2000). Networks that consisted of multiple components were accounted for by calculating network density for each component individually, and then determining the weighted density average based on component size. We made use of the functionality available in the statnet suite (Goodreau, Handcock, Hunter, Butts, & Morris, 2008) available in the R statistical environment (R Development Core Team, 2018) in these calculations.

**Network degree centralization.** The extent to which joint member ties are organized around one or few nodes in the network –indicating joint foci on few technological trajectories– is expressed by the measure of degree centralization (Freeman, 1978). We calculate this measure with the normalized degree centrality scores of each consortium, to account for differences in network size. Networks that consisted of multiple components were accounted for by calculating degree centralization for each component individually, and then determining the weighted average based on component size. We made use of the functionality available in the statnet suite (Goodreau et al., 2008) available in the R statistical environment (R Development Core Team, 2018) in these calculations.

**Control variables.** In addition to the parameters derived from the two key aspects of the network architecture concept, we included a year variable as a control in our analysis. As noted earlier, the movement of a network through the state space is –amongst others– determined by initial conditions of the network itself (Bickhard & Campbell, 2003; Makadok & Walker, 2007). Including a year variable in our analyses accounts for this, as it assumes path-dependence in the effect of time (Gulati & Gargiulo, 1999).

**Data analysis**
Different authors have pointed at the complexities and challenges involved in the development of methods needed for analysing longitudinal network data, especially because of the path-dependency of subsequent network observations (Faust & Skvoretz, 2002; Stokman & Doreian, 1996). The dominant approach that has emerged in the context of research on tie formation, is
to represent network dynamics as a stochastic process (Lusher, Koskinen, & Robins, 2013; Rose Kim, Howard, Cox Pahnke, & Boeker, 2016). Yet, the ERGMs and SAOMs involved in these approaches are less suitable for analysing complete interorganizational network dynamics for several reasons. First, ties in the networks we consider in this paper are undirected, yet to fully unleash the potential of said models these ties need to be directed. Second, considerable technical challenges are faced when handling large networks (Kleinbaum, Stuart, & Tushman, 2013; Sytch & Tatarynowicz, 2013) as well as networks that are characterized by node entry and exit (Huisman & Snijders, 2003; Krivitsky, Handcock, & Morris, 2011). Both are salient aspects of the networks that are we study in this paper. In practice, these issues result in the need for a considerable amount of computational power and time, which is not offered by the current state of technology.

Given that the use of these sophisticated techniques currently is impossible for the network data focused at in this paper, we resort to an approach that allows us to capture the movement of a network through the state space. We employ the statistical technique of latent profile analysis. This is an exploratory technique that we use to probe whether the consortium networks systematically align in such a way that they form distinct states. Although in the past clustering methods such as hierarchical or k-means clustering were used to derive latent groupings from data (Kassambara, 2017; Short, Payne, & Ketchen, 2008), latent profile analysis provides a comparatively more reliable estimation of distinct states.

Latent profile analysis is a model-based approach that offers various model selection tools, and results in a probability-based classification through estimating a posterior probability of membership that can be evaluated using goodness of fit indices (Ebers & Oerlemans, 2013; Haughton, Legrand, & Woolford, 2009). In its essence, latent profile analysis can be thought of as addressing a missing data problem (Oberski, 2016). In this paper, we observe several parameters and a control variable for 156 networks, and suspect that these cluster in distinct states. Our expectation is that, if our states are defined well (i.e. all relevant parameters are
specified), subsequent network states generally will form smooth trajectories within the state space (Bickhard & Campbell, 2003). These states, however, are not observed when model estimation starts. As estimation progresses, parameters are devised that seek to identify the smallest number of unobserved states that is sufficient to account for the relationships among the observed indicators (Ebers & Oerlemans, 2013). Different packages are available for latent profile analysis (i.e. the commercially available package Latent Gold® (Vermunt & Magidson, 2016), and two packages available in R, MCLUST (Scrucca, Fop, Murphy, & Raftery, 2016) and poLCA (Linzer & Lewis, 2011). A comparison of these packages (Haughton et al., 2009) concluded that MCLUST is most suitable for continuous data, which is characteristic of the parameters we focus at in this paper. Hence, we use the MCLUST package for our analysis.

Results
Descriptive statistics and correlations
Table 1 shows the descriptive statistics and correlations for the state parameters and the control variable. Although not included in the analysis, we also included different technology field dummies in this Table because these are used for grouping the results of the latent profile analysis. Means of these dummies are similar, indicating that network observations are equally spread across technology fields. Marked differences between technology fields can be seen when one considers the correlations between field dummies and state parameters. With respect to the correlations between parameters that do not denote technology fields, one can deduct a clear growth pattern when assessing the correlations between the year variable and the variables for size, node entry, node exit and degree centralization. This is not the case for density, which appears to develop independently from the progress of time. Correlations among size, node entry and node exit show a consistent pattern: larger size means more entry as well as exit, and more entry as such also implies more exit. The behaviour of these parameters in relation to density and degree centralization, as well as the correlations between the latter two sketch a
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>s.d.</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Chemistry……………...</td>
<td>.14</td>
<td>.35</td>
<td>0</td>
<td>1</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Civil engineering……..</td>
<td>.14</td>
<td>.35</td>
<td>0</td>
<td>1</td>
<td>-.16*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Electrical engineering…</td>
<td>.15</td>
<td>.36</td>
<td>0</td>
<td>1</td>
<td>-.17*</td>
<td>-.17*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Instruments…………....</td>
<td>.13</td>
<td>.34</td>
<td>0</td>
<td>1</td>
<td>-.16*</td>
<td>-.16*</td>
<td>-.16*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Life sciences…………...</td>
<td>.15</td>
<td>.36</td>
<td>0</td>
<td>1</td>
<td>-.17*</td>
<td>-.17*</td>
<td>-.17*</td>
<td>-.16*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Mechanical engineering.</td>
<td>.14</td>
<td>.35</td>
<td>0</td>
<td>1</td>
<td>-.16*</td>
<td>-.16*</td>
<td>-.17*</td>
<td>-.16*</td>
<td>-.17*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Medical technology…….</td>
<td>.15</td>
<td>.36</td>
<td>0</td>
<td>1</td>
<td>-.17*</td>
<td>-.17*</td>
<td>-.17*</td>
<td>-.16*</td>
<td>-.17*</td>
<td>-.17*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Year………………….</td>
<td>1993.35</td>
<td>6.47</td>
<td>1982</td>
<td>2004</td>
<td>.01</td>
<td>.01</td>
<td>.02</td>
<td>.04</td>
<td>.02</td>
<td>.01</td>
<td>.02</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Network size……………</td>
<td>47.71</td>
<td>32.36</td>
<td>3</td>
<td>141</td>
<td>.31**</td>
<td>- .35**</td>
<td>.10</td>
<td>.23**</td>
<td>.36**</td>
<td>-.41**</td>
<td>-.25**</td>
<td>.50**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Node entry……………</td>
<td>7.26</td>
<td>5.68</td>
<td>0</td>
<td>31</td>
<td>.25**</td>
<td>-.30*</td>
<td>.14</td>
<td>.10</td>
<td>.33**</td>
<td>-.29**</td>
<td>-.24**</td>
<td>.22**</td>
<td>.69**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11. Node exit…………….</td>
<td>5.17</td>
<td>5.06</td>
<td>0</td>
<td>26</td>
<td>.23**</td>
<td>-.22*</td>
<td>.05</td>
<td>.12</td>
<td>.27**</td>
<td>-.24*</td>
<td>-.20*</td>
<td>.52**</td>
<td>.70**</td>
<td>.41**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12. Density…………….</td>
<td>.25</td>
<td>.11</td>
<td>.07</td>
<td>.67</td>
<td>-.13</td>
<td>.27**</td>
<td>.42**</td>
<td>-.36**</td>
<td>-.32**</td>
<td>.13</td>
<td>-.02</td>
<td>-.13</td>
<td>-.42**</td>
<td>-.30**</td>
<td>-.26**</td>
<td></td>
</tr>
<tr>
<td>13. Degree centralization..</td>
<td>.33</td>
<td>.14</td>
<td>.08</td>
<td>1</td>
<td>.12</td>
<td>.03</td>
<td>.01</td>
<td>-.27**</td>
<td>-.24**</td>
<td>.26**</td>
<td>.09</td>
<td>-.23**</td>
<td>-.35**</td>
<td>-.32**</td>
<td>-.21**</td>
<td>.59**</td>
</tr>
</tbody>
</table>

\(^1 n = 156. \, ^* p < .01; \, ^p < .05.\)
more intriguing picture: while one intuitively would expect these measures to move in opposite directions, the found correlations suggest this is not the case. Instead, both move in the same direction and are negatively associated with node entry and exit: more density is associated with more centralization of the network, and this structure emerges under conditions of low node turnover.

Results of Latent Profile Analysis

Table 2 shows the average scores and standard deviations of the parameters in our framework for each found class. In addition to the Formation-state, which we constructed based on observations of outliers in the early years of the development of each network, four distinct states were identified by the conducted latent profile analysis. The covariances of each state have ellipsoidal distributions that are equal in both volume and shape but vary in orientation. The BIC of the final model was 1,840, which was the lowest of all 14 models considered. Hence, this model (the so-called EEV-model, see Scrucca et al. (2016) for an explanation of this model as well as the other 13 possible models) was selected. Considerable data exploration preceded the estimation of this final model. As expected, multivariate outliers were detected both in the initial stages of network development (28 observations) and the post-formation...
stages (28 observations). After careful deliberation, we decided to leave out from the final model those networks causing outliers due to being in the initial stages of network development, and separately label the state of these networks upfront. The label used for this additional state was ‘Formation’. Post-formation outliers were included in the dataset, and an auxiliary variable denoting outlier status (i.e. outlier or no outlier) was included as one of the latent profile predictors.

Table 3 provides an overview of the movement of the found states through the state space per technology field on the basis of the yearly calculation of the network state based on the five dimensions. We infer three main observations. First, we deduce that considerable differences exist in network dynamics between technology fields. Yet, a common pathway can be identified: despite variations, this pathway starts from the Formation state, via the state of Growth, to the state of Stability. This exact pathway can be observed for the fields of Electrical engineering and Instruments. Variations on this pathway are seen in the developmental patterns for the fields of Chemistry (where the Growth state is skipped, and networks move right away to the state of Stability), Life sciences (where the state of Stability is interrupted by a 9-year episode of Disintegration) and Medical technology (which starts with the Formation and Growth stage but does not transition to the state of Stability). The first two stages can also be seen in the network development of the fields of Civil engineering and Mechanical engineering. However, instead of transitioning to the state of Stability, both field networks start alternating between the states of Growth and Stagnation after they have first reached the Growth state.

Second, considerable variation exists between field networks when we consider the duration of states. The fields shown in the first five columns of Table 3, for example, are characterized by a Formation stage that takes at most four years. The other two fields (i.e. Mechanical engineering and Medical technology), on the other hand, reside in this state for six and seven years, respectively. No clear patterns can be deciphered from these state durations. Whereas, for example, the fields of Electrical engineering and Life sciences have Formation
states that last an equal number of years, the latter field network remains considerably shorter in the subsequent Growth state compared to the first. This insight is important, because as we will describe shortly the nature of each state differs considering our expectations regarding technology dynamics. For this specific comparison, we described earlier that except for network size, the Growth and Stability state are relatively comparable with respect to the parameters of node entry, node exit, and degree centralization, yet networks in the state of Stability have lower density levels compared to networks in the state of Growth.

Third, certain state sequences are observed more often compared to others, and some sequences are not observed at all. Figure 2 summarizes the prevalence of, and common pathways between states, with node size denoting state prevalence and arrows denoting the direction in which state changes can take place. This figure clearly shows the earlier described common pathway from Formation, via Growth to Stability. It also shows the mentioned shortcut from the Formation state directly to the Stability state. State changes from the Growth state to the state of Disintegration, however, are not possible: networks do not instantly quadruple in size and reconfigure profoundly. Other unobserved state changes are the state change from the Stability state back to the state of Growth or to the state of Stagnation. This implies lock-in: none of the networks that get into the stability state subsequently move to one of the other states, except for the Life sciences network, which disintegrates for some time before switching back to the stability state. We will discuss in the next section how the frequent observation of some state changes and the infrequent observations (or lack thereof) of others can be interpreted considering the underlying technology field dynamics.
### TABLE 3

**States and movement through the state space over time per technology field**

<table>
<thead>
<tr>
<th>Year</th>
<th>CH</th>
<th>CE</th>
<th>EE</th>
<th>IN</th>
<th>LS</th>
<th>ME</th>
<th>MT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1983</td>
<td>Formation</td>
<td>Formation</td>
<td></td>
<td></td>
<td>Formation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1984</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Formation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1985</td>
<td></td>
<td>Growth</td>
<td>Growth</td>
<td></td>
<td>Growth</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1986</td>
<td>Stability</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1987</td>
<td></td>
<td>Stagnation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1988</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Growth</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1989</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Growth</td>
</tr>
<tr>
<td>1990</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Stability</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1991</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Stagnation</td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Stability</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1993</td>
<td></td>
<td>Growth</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1994</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td></td>
<td></td>
<td>Stability</td>
<td></td>
<td>Disintegration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1996</td>
<td></td>
<td>Stagnation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1998</td>
<td></td>
<td>Growth</td>
<td></td>
<td></td>
<td></td>
<td>Growth</td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td></td>
<td>Stagnation</td>
<td></td>
<td></td>
<td></td>
<td>Stagnation</td>
<td></td>
</tr>
<tr>
<td>2001</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2002</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Growth</td>
<td></td>
</tr>
<tr>
<td>2003</td>
<td></td>
<td>Growth</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2004</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Stability</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

2 Key to the abbreviations: CH = Chemistry, CE = Civil engineering, EE = Electrical engineering, IN = Instruments, LS = Life sciences, ME = Mechanical engineering and MT = Medical technology.
Earlier, we linked the Formation state to the establishment of a new technology field network. Figure 2 also offers insights regarding the link between network dynamics and the other stages of technological development. Theoretically, we expect stability over time in the population parameters as well as high levels of network density and degree centralization which reflects that few consortia have obtained a dominant position in the network, guiding the efforts of other consortia around few technologies. The relative long uninterrupted time frames with which the Stability state sustains indicates that this could be the network state in which this occurs in the network, although especially network density is lower compared to the other states. The occurrence of a technological discontinuity is reflected in the state of Disintegration: its low prevalence and considerable increase in network size in combination with drops in the structural parameters and changes in the population parameters reflects all characteristics of such a breakthrough innovation. The states of Growth and Decline are more difficult to align with our theoretical expectations: even though the frequent alternating occurrence of these

---

3 Key: I = Formation, II = Growth, III = Stagnation, IV = Stability, V = Disintegration.
states, suggesting periods of technological ferment and maturity, these states are not preceded by the network state we associated with technological discontinuities, Disintegration.

**Discussion and conclusion**

Whereas the existing literature suggests a heterogeneous development of different technology field networks, innovation policy aimed at the formation and development of such networks is surprisingly homogeneous. As networks might develop in different ways and with different speeds, this homogeneity can be problematic. The question if network dynamics differ between technology fields, however, has hitherto remained unanswered. Through incorporating the two aspects of the definition of network dynamics by Ahuja et al. (2012) in a conceptual model that revolved around the heuristic of a network state, and linking this state to technology field dynamics, we mapped network dynamics in terms of the pathway followed by a network through the space state. The network dynamics of 7 technology field were described using this model. This allowed us to identify the five states of Formation, Growth, Stagnation, Stability and Disintegration.

Describing the dynamics of networks using state changes suggests the existence of a basic pathway from formation, via growth, to stability. Alternations of this pathway do occur, however, for example shortcuts from formation to stability, a network going back and forth from growth to decline, or networks switching from a state of stability to disintegration. This is the first indication that network dynamics indeed differ between technology fields. Our analysis also reveals considerable differences between networks with respect to the duration of different states. For example, whereas networks in the field of Chemistry and Medical technology can be characterized by few states that last for longer time periods, the fields of Electrical engineering and Instruments display more variation. The sequence of states for the fields of Civil engineering, Life sciences and Mechanical engineering deviates even more from this basic pathway, as none of these networks reach the state of Stability. This is the second indication that network dynamics indeed differ between technology fields.
Theoretical and practical implications

The number of distinct states revealed by our analysis is limited, and the sequences of state changes followed through the state space do fit our tentative theoretical expectations regarding the link between technology dynamics and network dynamics. Both are an indication that most of the relevant parameters needed for the identification of states are specified (Bickhard & Campbell, 2003). Indeed, even though a direct comparison is impossible, overlaps are detected when we compare our findings regarding the duration of states and state transitions in the field of Electrical engineering and Life sciences with the existing literature. For example, in one of the major sub sectors of the field of Electrical engineering, the information technology industry, Hanaki, Nakajima, and Ogura (2010) show that the IT network shows considerable growth from 1991 to 1995, with a trend towards a structure characterized by increasing density and local centralization (i.e. a small-world network). This trend coalesces with the evolutionary growth state in which our Electrical engineering network is from 1985 until 1995, before it switches to the state of stability. Indeed, this state is characterized by high density and centralization levels, and it would be interesting to extend the network analysis of Hanaki et al. (2010) to years beyond 1995 in order to see if that network also transitioned to this state of stabilization around that time.

Several authors have investigated the evolution of networks in the Life sciences field. Their findings match well with ours, even though a discrepancy in explanations exists. The global trend in this field described by others is that it shows a steady growth as from 1975, with increasing density levels (Orsenigo et al., 2001; Roijakkers & Hagedoorn, 2006). Whereas the field is dominated by its originators (small dedicated biotech firms) in the 1980s, the 1990s are marked by the entry of large, established pharmaceutical companies that tend to get more and more dominant as this decade progresses (Gay & Dousset, 2005; Gilising et al., 2016; Orsenigo et al., 2001; Roijakkers & Hagedoorn, 2006). This is in line with the sequence of formation states that we observe for this field from 1982 to 1994. The pharmaceutical sector underwent
a period of consolidation in the mid to late 1990s, marked by mergers and acquisitions (Powell et al., 2005). Our analysis reveals the state of Disintegration in this period. As we explained in the theoretical section of this paper, later incumbents from other technology fields can overtake an emerging one. Hence, a possible explanation for the state of Disintegration in the field of Life Sciences is that a consolidation wave took place from incumbents from other technology fields that overtook this field.

In this paper we applied an empirical approach towards discerning distinct developmental states and find that states can be predicted using relevant parameters, yet state changes are unpredictable. This raises the question to what extent theorizing regarding change can take place. Scholars have classified the question if technology indeed changes through a cyclical process marked by stages of discontinuity, ferment, maturation and dominant design as important, as it has major ramifications for the competencies of incumbent firms (Murmann & Frenken, 2006). van de Ven and Poole (1995) propose four distinct approaches towards theorizing about change in organization studies: life-cycle, teleological, dialectical and evolutionary (van de Ven & Poole, 1995). None of these change patterns are clearly revealed by our analysis. The common pathway that we found and that leads from Formation, via the state of Growth to the State of Stability suggests linearity (i.e. life cycle) in network dynamics, yet the differences between fields are too large to be conclusive about this. In addition, our theoretical arguments propose a cycle (evolutionary), yet this is revealed for none of the field networks as well. This suggests that theories of change can only be developed fruitfully for shorter time frames, and the topic should be approached empirically once these time frames, and with the associated uncertainty, get longer.

We claimed in the introduction that a major practical implication of our work is that it allows for a more targeted specification of policy measures directed at external network orchestration. According to Mohrman et al. (2006), policy can affect field networks in two distinct ways. First, it can impact variation, selection and retention processes in the technology
field through regulating node entry and exit levels. Obviously, the direction in which network change should take place depends on which network states are most conducive for joint innovation. In general, however, we can say that our model provides clear levers for inducing state transitions. Should one desire to get a network out of its state of Decline, allowing more consortia to enter through making more funds available for that specific technology field would be a strategy. In a similar vein, networks can be taken out of a state of disintegration by reducing both node entry and node exit. The latter can be achieved by for example funding consortia that follow-up consortia that have not generated substantial results (and could be considered a failure), yet simply might need more gestation time to generate these results. Given a fixed budget, making more resources available for one technology field implies that less resources become available for other fields with its corresponding impact in network dynamics, however.

The second way in which policy can shape networks is through affecting linkages in the network via requirements for research proposals and through funding of various kinds of cross-over or within-field institutes (Mohrman et al., 2006). In this area we see opportunities in particular with respect to funding consortia that function as bottom-up network orchestrators, or network “weavers” (Ingram & Torfason, 2010) should one desire to get networks in the relative centralized state of Growth, for example. This could also aid the reliability of networks (Berthod, Grothe-Hammer, Müller-Seitz, Raab, & Sydow, 2016), even in times of turmoil, such as the state of Disintegration. Lastly, network structure can be affected through mandating specific joint consortium ties, although here the question is to what extent these mandated ties will be activated.

**Strengths, limitations and suggestions for future research**

Taken together, both our research approach as findings provide a point of reference for existing and future research on the topic of the hitherto relatively anecdotal field of research on complete interorganizational network dynamics. Despite the strong data basis that has driven
our research, it is not without limitations. A recent critique on interorganizational network research that has been voiced is that not enough is done to overcome the implicit assumption of knowledge circulating freely within these networks (Ghosh & Rosenkopf, 2015). Frictions in interorganizational networks exist, for example due to the nature of knowledge and the composition of ties. An important limitation of the current study is that we do not consider properties of ties in our analysis. For example, even though ties in the networks studied are valued (i.e. the number of joint member ties between any two consortia), tie strength is binarized in our analysis in order to avoid additional complexities with respect to calculating density and degree centralization for valued graphs (Scott, 2000). One could argue, however, that switches between states become more difficult at higher average levels of tie strengths in the networks under consideration. Hence, a fruitful extension of our model would be to consider the role of tie strength. For example, can we delineate different states if we consider average tie strength in the latent profile analysis, and what is the relation between average tie strength in a network and the number of dominant designs focused at in a technology field network?

Another general issue in research on interorganizational networks related to ties is that not much attention is given to the changing states of these ties as such: not all ties are alive and equally available at a given point in time. Instead, they could for example be activated periodically, or remain in a dormant state for long periods prior to activation (Maclean & Harvey, 2015). It is hard to get data on these aspects from secondary data, but one strategy could be to scan minutes of meetings of the users committee, for example. Such a strategy has been employed successfully by Chappin (2008). In addition, a process-based approach to studying network dynamics could at least bring more general insight in the way consortium members perceive these joint member ties and in the reasons for, and frequency of activation of these ties. For example, antecedents of tie activation or tie deactivation could be studied, or
the relation between the state of a tie and the type of knowledge that is being transmitted through it.

Lastly, at the start of this paper, we mentioned that our research question was simple, yet difficult to answer. Although we fruitfully applied the idea of network states and their pathway through state spaces, such descriptions should be subject to questions and further analysis (Bickhard & Campbell, 2003). Indeed, our research findings raise many more questions, as reflected in the above discussion. Even though the challenge in studying network dynamics will remain requiring sufficient data, future research that builds forth on our approach should especially focus more on the link between the movement of a network through the state space and the development of its underlying technology base.
References


