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The bioeconomy has become a central concept in many strategies for future economic development, emphasising an increasing need for collaboration across industries and sectors for innovation. This paper unpacks aspects of collaboration in the bioeconomy by looking at the development of innovation networks for biorefinery technologies from 2004 to 2014 based on innovation project data from Swedish public funding agencies using a stochastic actor-oriented model for network analysis. The analysis shows that although the network grew significantly during the time period, indicating an increasing interest in biorefinery technology innovation, inter-sectoral collaboration is not favoured over intra-sectoral collaboration. As is known from previous work on social networks trust-building is a key driver for collaboration, as actors tend to form collaborations with previous partners or indirectly connected partners, creating clustered networks.

Keywords: innovation; social network analysis; bioeconomy; biorefineries

Introduction

The concept of a bioeconomy is increasingly ascribed a key role in the development towards a sustainable society (Bugge, Hansen, and Klitkou 2016) and seen as a key part of the solution to multiple grand challenges (Coenen, Hansen, and Rekers 2015). While multiple competing definitions of a bioeconomy exist, the bioeconomy can generally be understood as ‘an economy where the basic building blocks for materials, chemicals and energy are derived from renewable biological resources’ (McCormick and Kautto 2013, 2590). In addition to positive impacts on climate change mitigation following from a substitution of bio-based for fossil-based resources and energy, the bioeconomy is believed to contribute to overcoming grand challenges related to food security, health, industrial restructuring and energy security (Ollikainen 2014; Pülzl, Kleinschmit, and Arts 2014; Richardson 2012) although concerns about its simultaneous contribution to

increasing price volatility, risk of over-exploitation of natural resources and spatial inequality have been raised by some authors (Ponte 2009; Swinnen and Riera 2013; McCormick and Kautto 2013).

Consequently, specific bioeconomy policies have been formulated by multiple international (OECD 2009, European Commission 2012) and national governmental organisations (see Staffas, Gustavsson, and McCormick 2013 for a review). While the strategies have different operationalisations of the bioeconomy, ranging from an emphasis on industrial biotechnology to one on resource efficiency, they do share the understanding of the bioeconomy as an indispensable part of our future society, highlighting the role of the bioeconomy as a powerful meta-discourse (Pülzl, Kleinschmit, and Arts 2014; Bugge, Hansen, and Klitkou 2016). Irrespectively of the exact understanding of the bioeconomy, a number of key characteristics of bioeconomy innovation processes are frequently emphasised, specifically, the increasing need for collaboration across industries and sectors.

Firstly, collaboration between actors from different industries is assumed to be of increasing importance in the development towards a bioeconomy. While the bioeconomy itself by many definition spans across industrial boundaries, it is also frequently highlighted that the development of innovations, which will facilitate the transition to a bioeconomy, requires collaboration between actors from different industries (Wield et al. 2013; Ollikainen 2014), an aspect which is also recurrently emphasised in policy documents (McCormick and Kautto 2013). To exemplify, the European Commission (2012, 8) places ‘cross-sectoral research and innovation’ as a key element in its bioeconomy action plan. This mirrors calls for multi-disciplinary bioeconomy research, which have previously been made by the European Commission (see Levidow, Birch, and Papaioannou 2013). Furthermore, in addition to intensifying

collaboration across industries, it is also suggested that collaboration between firms of different sizes is increasingly important for innovation processes in the bioeconomy. For instance, SMEs are considered to play an important role for innovation in the biorefinery field, in particular in relation to development of new bio-based product markets which currently are of very limited size, such as pharmaceuticals or fine chemicals (Menrad, Klein, and Kurka 2009).

Secondly, beyond private sector involvement, increasing collaboration between actors from different sectors is also repeatedly stressed. It is argued that innovation in the bioeconomy necessitates new partnerships between various types of actors, from firms and research institutions to policymakers, regulators, and stakeholder groups (Wield et al. 2013). This partly reflects the need for further advances in applied research in biotechnology and other related fields. As argued by Zilberman et al. (2013, 100) 'we expect the link between university research and private sector innovation to be crucial in the development of the bioeconomy' and this is indeed also stressed in many bioeconomy strategies (Staffas, Gustavsson, and McCormick 2013). However, it also reflects an increasing emphasis on the role of users of knowledge in the innovation process (Wield et al. 2013). Importantly, this is not considered to be limited to the parts of the bioeconomy which are directly related to the production of consumer goods, such as food production (see e.g. Levidow, Birch, and Papaioannou (2013) on the EU's 'fork to farm' research programme), but also involves industries such as life science where the innovation process has traditionally been driven by research-push (Wield et al. 2013).

In this way, certain characteristics of innovation processes in the bioeconomy – them necessitating more collaboration between actors of varying sizes, across industries and sectors– are repeatedly highlighted in academic work and in policy documents.

However, there is a lack of systematic assessment of the extent to which these characteristics are indeed found in bioeconomy innovation processes. In fact, most studies that put forward these suggestions do so based on little or no empirical evidence. To exemplify, Zilberman et al. (2013) refer to two collaborations on biofuels development between universities and major oil companies as an argument for the growing importance of industry-university collaboration in the bioeconomy.

In this paper, our aim is to take a first step in examining if these ascribed characteristics are indeed typical of bioeconomy innovation processes. We do this by empirically analysing the network of actors involved in biorefinery innovation projects in Sweden from 2004 to 2014. Biorefineries, understood as 'an overall concept of a processing plant where biomass feedstocks are converted and extracted into a spectrum of valuable products' (U.S. Department of Energy - Office of Energy Efficiency and Renewable Energy 1997), are repeatedly argued to play a key role in the transition to the bioeconomy, leading to a growing innovation system around biorefinery technologies (Bauer et al. 2017). In a Swedish context, forestry plays a key role in the transition to a bioeconomy, and literature specifically on this industry also highlights the need for increasing collaboration across industries, sectors and national boundaries (Hansen and Coenen 2017). As argued by Kleinschmit et al. (2014, 407), 'diminishing the traditionally strong actor coalitions of the forest sector' may be favourable to facilitate the transition into the bioeconomy. Thus, it is argued that a central aspect of the transition of the forestry industry to the bioeconomy is sufficient public support for innovation and demonstration projects on biorefinery technologies (Fevolden et al. 2017; Karltorp 2014; Ollikainen 2014). Echoing this, Kearnes (2013) highlights the importance of acknowledging the key role played by intermediaries such as research councils in translating high-level strategic purposes around the bioeconomy to actual

development of the field itself. Consequently, in this paper we analyse Swedish biorefinery innovation projects that have received public support in the period. The development of forest biorefineries is dominated by Research Development and Innovation (RDI) activities rather than actual operations and production of commercial scale facilities. It is therefore an area dominated by significant research activities, sponsored by both conventional academic research councils as well as more applied RDI funding schemes available also for research institutes and firms. Support for the bioeconomy and biorefinery technologies has become an important part of Swedish innovation policy over the last decade (Palgan and McCormick 2016; Hellsmark and Söderholm 2017) and also a prominent development strategy among organizations from different industries and sectors. A reasonably large number of innovation projects and collaborations on the topic is thus likely to be found in the Swedish environment.

Collaboration Networks and Innovation

The understanding of innovation as an interactive process between multiple actors has been well-established since early work on innovation systems (Freeman 1987; Lundvall 1988). Such collaborations are of growing importance due to the faster diffusion of knowledge and the increasing technological complexity of the economy (Powell, Koput, and Smith-Doerr 1996; Amin and Cohendet 2004). Thus, it is now rare that all the competencies needed for innovation projects are available within a single organisation, implying an increased frequency and importance of participation in inter-organisational innovation projects (Grabher 2002; 2004). This has also led to an increasing focus on networks as important phenomena in organisational research (Borgatti and Foster 2003) and innovation studies (Van Der Valk and Gijsbers 2010), but only recently has the dynamics of networks attracted interest from researchers (Ahuja, Soda, and Zaheer

2012).

In this paper, we are in particular interested in understanding how firms from different industries engage in collaboration with other firms, universities, and research institutes. Compared to collaborations between partners from the same industry, inter-industry collaborations are characterised by certain challenges. As highlighted by Cohen and Levinthal (1990), absorptive capacity is needed to interpret and exploit new knowledge, and inter-industry collaborations require higher degrees of absorptive capacity. Consequently, differences in core markets and technologies make it difficult to cooperate effectively, and firms therefore tend to collaborate with partners having similar capabilities (Stuart 1998; Mowery, Oxley, and Silverman 1998). Furthermore, the propensity to collaborate with partners from the same industry is reinforced by the importance of previous collaboration patterns. Existing connections facilitate partnership formation by providing information about appropriate collaborators in the network and by reducing the risk of opportunistic behaviour (Gulati 1995; Gulati 1998). Consequently, partnerships are often created between former collaborators or organizations with shared connections (Guimera et al. 2005; Paier and Scherngell 2011; Autant-Bernard et al. 2007).

However, while intra-industry collaborations may be more effective, they may also lead to a limited degree of novelty (Nooteboom et al. 2007; Broekel and Boschma 2012). Thus, collaborations between similar firms may have a limited effect on innovativeness (Sampson 2007) and innovation diversity (Van Rijnsoever et al. 2015). This can be explained by a higher propensity to think along similar lines and thereby overlook superior alternatives (Frenken, Hekkert, and Godfroij 2004), as well as an inability to provide different resources, which can be recombined into new innovations (Fleming 2001; Jensen et al. 2007; Hansen and Winther 2011). Implicitly, the argument

made in work by academics and policymakers on the bioeconomy is that innovation in this field requires a particularly high degree of novelty creation, which necessitates increasing collaboration across industries, despite the negative effects on collaboration effectiveness.

Collaboration is thus important for innovation, but is simultaneously difficult and requires the investment of resources in managing these collaborations. There is a cost both for initiating (e.g. searching for and assessing possible partners, and negotiating terms) and for maintaining (e.g. increasing complexity of collaboration, and time spent on managing relationships) collaborations (Cantner, Conti, and Meder 2010). It is therefore not to be expected that the density of innovation networks will constantly increase as it evolves, but rather organisations will have to choose carefully which collaborations to maintain, leading to networks that are generally sparse but with denser clusters, as well as some highly connected organisations (Cowan and Jonard 2009).

Furthermore, organisations belonging to different industries and sectors may also have very different opportunities for and experience with collaboration across industries (Malerba 2002; Pavitt 1984). The forestry industry is characterised by a close relationship to a limited number of technology suppliers and equipment manufacturers, which play a key role for process innovation in the forestry industry. Conversely, multiple studies report difficulties for firms in this industry of forming collaborations with downstream firms in markets for new biobased products, which could potentially bring together competencies regarding handling and treatment of biomass with knowledge on consumer needs and commercialisation opportunities (Bauer et al. 2017; Chambost, McNutt, and Stuart 2009; Hansen and Coenen 2017; Näyhä and Pesonen 2014).

Methods and data

Statistical analysis of network evolution using stochastic actor-oriented modelling

We analyse the collaboration between different organisations as a dynamic social network. It is only recently that a more detailed understanding of how innovation networks form and evolve has been developed with the help of tools from complex systems and social network analysis (Pyka and Scharnhorst 2009). Several kinds of statistical models are available for analysing social networks, both for cross-sectional analysis, the possibilities and limitations of which were reviewed by Snijders (2011). The stochastic actor-oriented model (SAOM) used for this study was the SIENA model, implemented in R as the package RSiena[1].

The SAOM allows for the representation of network dynamics driven both by endogenous network processes, such as reciprocity and popularity, and exogenous influences defined by actor attributes, e.g. homophily or proximity effects. The model also allows for implementing representations of several of these processes in parallel, estimating parameters for their effect on the network evolution, and testing the significance of these effects (Snijders, van de Bunt, and Steglich 2010; Snijders 2017). In principle, the SAOM simulates the evolution of the network between the empirical observations and estimates parameters, for the mechanisms that drive the dynamic process. The use of SAOM for analysing inter-organisational collaboration was introduced by van de Bunt and Groenewegen (2007) and has been successfully used to analyse drivers for the development of knowledge and innovation networks (Balland 2012; Balland, De Vaan, and Boschma 2013).

Fundamental to the SAOM approach is the understanding of the network data as representing states, rather than specific events but there are also several important

assumptions underpinning the model (Snijders, van de Bunt, and Steglich 2010). Firstly, time is interpreted as being continuous between the observations, which can be understood as network panel waves, representing the state of the network at a given point in time. Secondly, the evolution of the network is the outcome of a Markov process, i.e. at each point in time changes depend only on the current state of the network. This means that actors in the network have no memory going back further than the previous state, and also that they cannot see beyond the next state. As one important aspect of collaboration is trust, which can be established in previous collaborations, this has to be included specifically in the model, which is described in more detail in the subsection on 'model specification'. Thirdly, actors control the formation of outward ties, connections from themselves to someone else in the network. This assumption is evident in terms of advice networks, in which actors unilaterally decide whom to ask for advice, but has to be modified for collaboration networks as actors cannot decide on their own with whom they collaborate, which is also discussed further in the subsection on 'model specification'. Finally, changes in the network are modelled as being incremental, meaning that ties change one at the time in the model, which can be understood as the process of incrementally building a project group.

Data on biorefinery technology innovation networks

We aim to capture a complete network of organisations engaged in forest biorefinery RDI in the analysis. We therefore started by identifying all relevant, recent projects that had received funding from the Swedish Energy Agency (STEM) – a main funder for biofuels and related RDI – and the Swedish Innovation Agency (VINNOVA). The underlying assumption of this choice was that every actor engaged in biorefinery RDI projects is likely to have participated in at least one project co-funded by either of these organisations. Aiming to capture the collaborations between all types of actors in the

networks we focused on these agencies rather than the research councils that fund strictly academic research.

Relevant projects were identified through the online project databases of STEM and VINNOVA. For all projects that had been co-funded by at least one non-academic organisation the submitted project applications as well as the grant approval letters were requested. The documents were used to identify the participating organisations, their role in and contribution to the project, key individuals, and connections to important pilot and demonstration facilities – information which was collected in a joint database. Large projects, with more than 10 participating organisations, were split into several projects following work package descriptions in the applications, as it is unreasonable to assume that all organisations in large projects actually collaborate with each other. Although it cannot be deduced from the project descriptions how closely the different actors in the project collaborate, edges are as mentioned above binary, the splitting of large projects reduces the otherwise very high tendency of clustering in the network. Even though splitting large networks, the data used is probable to slightly overestimate clustering due to the assumption that all partners collaborate with everyone else in the project. Information about the organisations, such as industry sector and size was collected from the national firm register. Some descriptive statistics of the dataset is shown in Tables 1 and 2.

Table 1. Descriptive statistics for the longitudinal data set.

Projects		**Organisations**	
Number of projects	112	Number of organisations	77
Average participants	4.02	Average projects per	5.84

per project		organisation	
Standard deviation	3.35	Standard deviation	5.71
Median	3	Median	4

Table 2. Sectoral identity of organisations in the network.

Sector	**Number of organisations**
Research	23
Consultancy and engineering	13
Energy	12
Forestry	10
Chemicals and petroleum	10
Machinery and equipment	4
Other	5

From the database, comprising all the projects, undirected one-mode networks were created, one for each year. The nodes of these networks are the organisations participating in projects that were active at some point during that year, and the edges are collaborations between two organisations, representing that two organisations both participate in an active project. Edges are undirected as they represent collaboration which is by definition a two-sided relationship, and for modelling purposes binary, i.e. indicating collaboration in at least one project. It was assumed that all project participants collaborate with each other during all the years in which a project is active. To have enough stability in the network evolution, the dataset was filtered to include only organisations that were part of at least two projects and thus reflecting the

organisations that have been engaging in biorefinery technology development more than as a peripheral partner.

During the studied time period the network is growing as the number of active organisations increases, but some organisations also choose to leave the network. Figure 1 shows the growth of the network during the studied period.

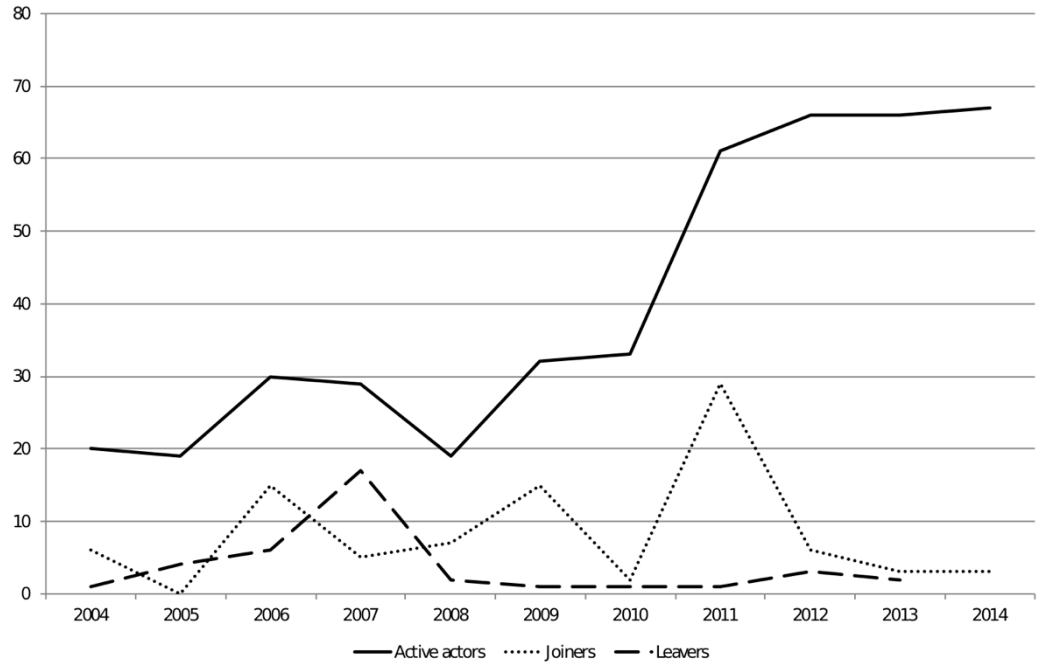

Figure 1. The number of organisations active in the network, joining and leaving the network during the studied period.

Table 3 shows the basic statistics of the changes in the network. Jaccard indices indicate the similarity between data points, e.g. between networks in different years and should preferably be larger than 0.3 (Snijders, van de Bunt, and Steglich 2010), but for two periods it is in fact lower. For the period 2010-2011 the low Jaccard index corresponds to a rapid growth of the network, in which case this is fully acceptable as the share of

remaining ties is very high. For the period 2007-2008 the Jaccard index is indeed low, but this was deemed to be acceptable as it is just one out of 10 periods included in the analysis and did not cause convergence problems.

Table 3. Changes in relationships during the evolution of the network.

Period	**0 → 1**	**1 → 0**	**1 → 1**	**Jaccard index**
2004-2005	0	9	68	0.883
2005-2006	63	18	50	0.382
2006-2007	9	41	72	0.590
2007-2008	19	63	18	0.180
2008-2009	44	5	32	0.395
2009-2010	3	10	66	0.835
2010-2011	289	5	64	0.179
2011-2012	133	7	346	0.712
2012-2013	58	49	430	0.801
2013-2014	20	95	393	0.774

Model specification

Since collaboration is not a one-sided relation, edges are (as previously mentioned) interpreted as being undirected. As tie formation in the actor-oriented model is originally depending only on the actor creating an outgoing tie, this must be modelled differently in the case of undirected ties. The most realistic way of describing the formation of a collaboration between two organisations is the model of unilateral initiative and reciprocal confirmation (van de Bunt and Groenewegen 2007; Balland, De

Vaan, and Boschma 2013). This specification represents a process in which an organisation takes initiative to collaborate with another organisation, but for the tie to be formed the second organisation has to agree on the collaboration. Thus, both organizations must see the collaboration as beneficial for the connection to be established.

As shown in Figure 1 the network grows significantly over the studied time period, i.e. more organisations join the network. The participation of organisations in the network for each year was modelled using 'structural zeros' for the years in which they did not take part in any projects, meaning that they were coded as not being available for any collaboration. Although more elaborate options for including information about joiners and leavers (Huisman and Snijders 2003) the simple and robust model of structural zeros was chosen as the information on exactly when the organisations were joining or leaving the network was not available.

Endogenous effects

The degree effect is the most basic effect in the model, representing the tendency to have ties at all and can be interpreted as the fundamental balance between benefits and costs of creating and maintaining collaborations with other organisations in the network (Snijders, van de Bunt, and Steglich 2010).

Popularity represents the tendency of networks to form global hierarchies with a few very important nodes with high status in the network. Popularity indicates that organisations prefer collaborations with other organisations that already have many ties. As the available data does not describe the forming of connections and the ties are seen as undirected, this means that popularity is important both for those actors initiating and

those accepting the collaboration. Popularity is modelled using the square root of degree of alters.

Network closure represents the tendency of organisations in the network to initiate collaborations with indirectly connected organisations, i.e. with whom they share collaborators. Shared partners are important for sharing information, building trust, and reducing uncertainty about collaborations with the other organisation (Cowan, Jonard, and Zimmermann 2007). Network closure is modelled using the geometrically weighted edgewise shared partners (GWESP) effect. The GWESP effect is a weaker effect than other transitivity effects that focus on triadic closure, as the contribution of additional indirect connections decreases with the number of shared partners. The GWESP tuning parameter α was set to log(2)=0.69 assuming that the additional effect of having more than two shared partners is very small.

Sector effects

As different sectors organise and collaborate in different ways, the sectoral identity of the different organisations is included as a binary covariate for the most important sectors. The sector effects can thus be interpreted as the increased or decreased propensity of firms from these sectors to engage in collaborations within the network. As increasing importance of cross-sectoral collaborations is one of the most emphasised aspects of the bioeconomy literature, we also include a binary dyadic covariate that indicates whether two organisations belong to the same sector or not. Sectoral identity was defined as industrial sectors, research (including universities and research institutes), and public sector.

Other effects

Trust between organizations cannot only be built by shared partners, but also from

previous experience of collaborations between organizations (Gulati and Gargiulo 1999). As trust and knowledge about partners is an important aspect of choosing partners, previous collaborations were included in the model as a changing binary dyadic covariate with a five-year dependency. This effect thus models an organizational memory of previous collaborations with other organizations which extends backwards five years, relieving the strict Markov chain assumption of no memory mentioned previously.

Results and benefits from collaborations may not be shared equally between the partners depending on what role they take in the project. If the organisation that takes the role of managing a project has greater access to the information produced in the project and thus gains more from the collaborative effort, this organisation may become more willing to engage in collaborations. An ego effect based on a changing binary covariate indicating those actors that are managing projects each year was therefore included.

Results and discussion

As shown in Table 4 the network grew rapidly from a rather stable network of 20-30 actors in the period 2004-2010 to become almost 70 actors by the end of the studied period, coinciding with a large increase in the average degree of actors in the network. This shows that more organizations were moving towards the field and that collaborations have indeed been seen as important for their innovation projects. The average clustering coefficient remains high throughout the period indicating that collaboration occurs mainly in densely connected subgroups in the network.

Table 4. Structural characteristics of the evolving network. Calculations made using Gephi algorithms.

Year	**Nodes**	**Edges**	**Average degree**	**Average clustering coefficient**	**Density**	**Diameter**
2004	20	77	7.7	0.87	0.41	4
2005	19	68	7.2	0.95	0.40	3
2006	30	113	7.5	0.81	0.26	3
2007	29	81	5.6	0.90	0.20	3
2008	19	37	3.9	0.83	0.22	5
2009	32	76	4.8	0.83	0.15	4
2010	33	69	4.2	0.86	0.13	6
2011	61	353	11.6	0.86	0.19	5
2012	66	479	14.5	0.82	0.22	4
2013	66	488	14.8	0.78	0.23	5
2014	67	413	12.3	0.80	0.19	5

Figure 2 graphically illustrates the growth and clustering of the network, illustrating the dominance of research institutions in the early years of the studied time period and the shift towards a more mixed network in later years.

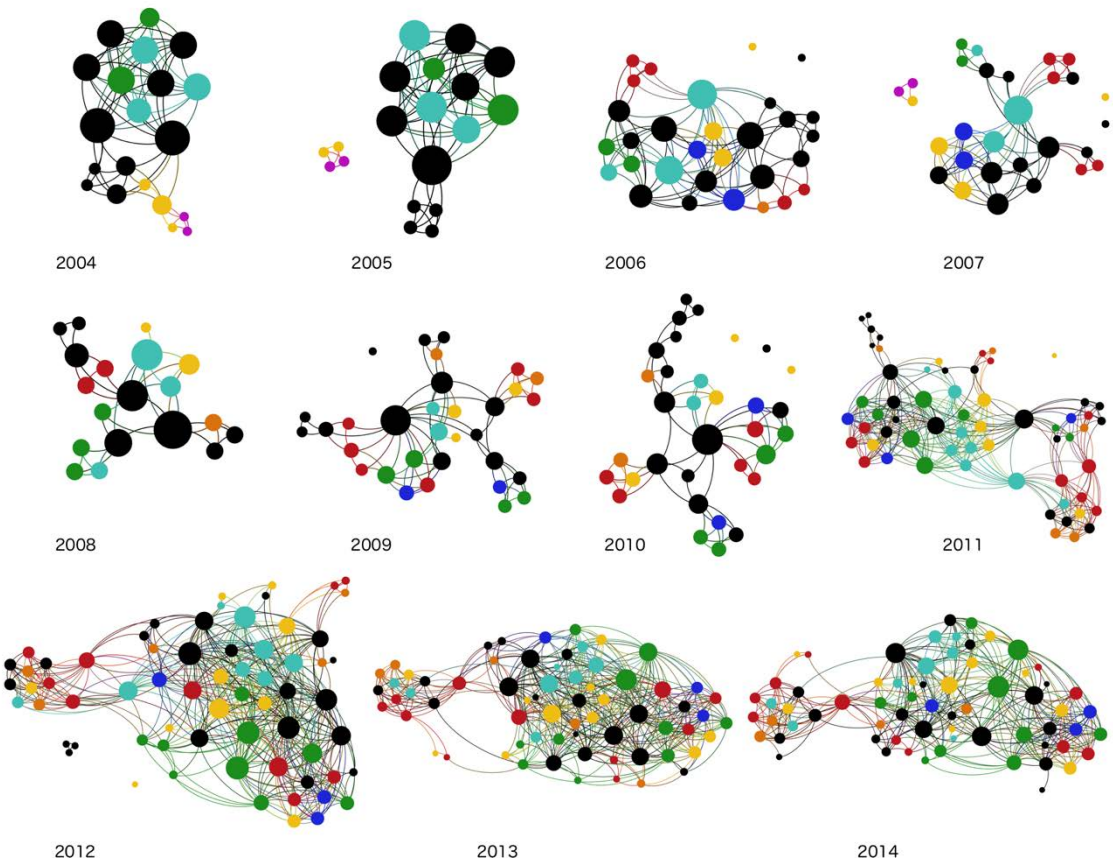

Figure 2. The studied networks during each year from 2004 to 2014. Node sizes based on degree value of nodes. Colours represent sector identity – black: research; blue: machinery; green: forestry; orange: other; purple: public; red: energy; turquoise: chemical; yellow: consultancy.

The results from the dynamic analysis, shown in Table 5, show that the propensity to change collaborations varies between the different years, with a few more stable periods in the middle. P-values for the rate parameters are not shown, as testing them toward a null hypothesis (that no change occurs) would be meaningless. The degree effect shows that the organisations do experience a cost of maintaining collaborations and thus it is not beneficial to simply maximise the number of collaborations. Network closure shows that collaborations with indirectly connected organisations are preferred, showing the importance of knowledge sharing and trust building through shared partners. The negative and significant value for popularity, indicates that collaborations in this

network are not hierarchical, i.e. that organisations do not all want to collaborate with a few very important organisations, but rather with different organisations in the network. This might be an indication of the fact that no single organisation is clearly ahead of all others, but that knowledge about biorefinery technologies is distributed among organizations.

Table 5. Parameter estimates from the statistical analysis of the dynamic network.

Parameter	**Estimate**	**Standard error**	**P-val**
Rate			
$\lambda_{2004\text{-}2005}$	0.440	0.196	
$\lambda_{2005\text{-}2006}$	3.350	1.557	
$\lambda_{2006\text{-}2007}$	1.618	0.490	
$\lambda_{2007\text{-}2008}$	1.834	0.972	
$\lambda_{2008\text{-}2009}$	0.871	0.402	
$\lambda_{2009\text{-}2010}$	0.635	0.238	
$\lambda_{2010\text{-}2011}$	2.939	0.815	
$\lambda_{2011\text{-}2012}$	3.087	0.505	
$\lambda_{2012\text{-}2013}$	3.150	0.427	
$\lambda_{2013\text{-}2014}$	3.231	0.408	
Endogenous effects			
Degree	-1.594	0.326	<0.001
Closure	2.817	0.364	<0.001
Popularity	-0.879	0.135	<0.001
Sector effects			

Forestry	-0.197	0.450	0.662
Chemicals & Petroleum	-1.322	0.424	0.002
Energy	-0.536	0.428	0.210
Machinery	-0.630	0.484	0.192
Consultancy & Engineering	-0.785	0.423	0.064
Research	-0.871	0.429	0.042
Similarity	0.160	0.125	0.200
Other effects			
Previous collaboration	0.455	0.198	0.021
Project management	0.529	0.188	0.005

As for the sectoral effects, the similarity effect is not a significant parameter, meaning that collaborations are seemingly not more likely to occur across sectors, as the literature has indicated would be important in the bioeconomy. There are however significant effects for specific sectors, where especially the chemical sector stands out as being significantly less prone to engage in collaborations. As biorefinery technologies many times imply radical changes to the production of chemicals and materials this effect can be seen to reflect a hesitancy of these actors to invest too much in very uncertain projects breaking with the traditional focus on process efficiency and scale effects that have dominated innovation in the chemical sector for a long time. Consultancy and engineering firms as well as research organisations also show a negative propensity to engage in collaborations, although the effect is much smaller than for firms from the chemical sector.

Previous collaboration is a significantly positive parameter, indicating that trust is an important issue for collaborations. Organisations that have been project managers are also significantly more likely to engage in new collaborations. One interpretation of this latter finding is that project managers gain more from the projects, and therefore are more willing to engage in new collaborations. Additionally, project managers typically take up a central role as knowledge integrators in innovation networks, bringing together partners with different competences, and are therefore more likely to collaborate widely.

Conclusions

The Swedish biorefinery technology innovation network grew significantly during the studied period. The study confirms that actors tend to form collaborations with actors they are indirectly connected to or have previously collaborated with and that the network is highly clustered, pointing towards the importance of trust building between actors. In line with previous studies, the analysis highlights that collaborations are costly to maintain and actors do consequently not seek to maximise the number of collaborations. Furthermore, the Swedish biorefinery innovation network is not dominated by a few centrally placed organisation and can thus be characterised as non-hierarchical.

Regarding the different sectors, we identify few significant effects apart from the strongly negative attitude of actors from the chemical petroleum industry showing that they are still not a core part of the field which has largely been focused around forestry industry actors. Our analysis does not provide insights into the reasons for the low collaboration propensity of actors in the chemical industry, despite increasing attention to bio-based chemicals and plastics. We suggest that future research should investigate

if sectoral characteristics of the industry, such as very high capital intensity and dominance of fossil feedstocks, are important barriers to entering biorefinery collaboration. We do not find inter-sectoral collaboration being favoured over intra-sectoral collaboration in the field, indicating that some of the earlier literature on the bioeconomy may have overestimated the importance of such collaboration, although additional research is needed to provide more evidence.

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Notes

1. The RSiena package and detailed documentation is freely available for download on https://www.stats.ox.ac.uk/~snijders/siena/
2. Gephi is a software for network visualization and analysis, freely available for download on https://gephi.org

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