Exploring Innovation Ecosystems as Networks: Four European Cases

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Abstract

More often than ever before, innovation takes place in the context of innovation ecosystems. New data, tools, and questions are available for insights on latent structures within innovation ecosystems. Used in concert, socially constructed data and network analysis afford new insights to compare and analyze the structure and dynamics of innovation ecosystems. In this article, we apply a novel approach for exploring innovation ecosystems through networks. Moreover, we investigate whether this new way of measuring innovation produces similar results compared to more traditional indicators, here Innovation Union Scoreboard. We conclude that network analysis of socially constructed data yields into results that are comparable to traditional innovation indicators and, importantly, allows completely new insights into the system-level structure of the innovation ecosystem. The new views allow and indeed call for new ways to conduct decision-making in the context of innovation ecosystems.

1. Introduction

Innovation is widely recognized as the critical source of competitive advantage and growth in global economy, and competitiveness is linked with differentiation and added value as perceived by customer [1]. Consequently, the ability to assess and measure the progress and impact of innovation efforts is seen important, though challenging, as any wish to manage innovation more explicitly. It has even been suggested that better measurement could possible contribute to competitive advantage [2].

There exist many indicators based on the harmonized sets of innovation concepts that focus on measuring innovation activities at the firm or organizational level, as well as taking on a broader macro-level look a usually national level, captured for example in gross domestic product. The traditional science, technology and innovation (STI) indicators—such as S&T personnel, patents, and quality change—have been complemented with so called DIU (doing, using and interacting) indicators such as integration of functions, cooperation with customers, and interdisciplinary workgroups [3,4]. In addition, there are emerging indicators that take into account knowledge intangibles, clusters and networks, management practices, and system dynamics [5]. In all, there is a transformation from analog to digital indicators of innovation [6]. Furthermore, due to challenges of measuring, individual indicators have been developed toward composites of perceived components of innovation, such as the European Union Innovation Union Scoreboard and Massachusetts Innovation Index that rank regions or nations with respect to their degree of innovation, and toward frameworks that address the different phases and areas of innovation [7,8].

Overall, there remains an assortment of challenges for innovation measurement. For example, post-hoc characteristics of measuring performance [2], difficulties in dealing with intangibles and value-based arguments, difficulties in integrating sustainability to formal decision making system [1], strong linkages of innovation processes to the factors of time and context, seldom addressing team level innovation [2]; and lack of data and subsequent regional level measurements [9] have been mentioned.

The process of innovation is complex, taking place in the complex world. However, innovation indicators are considered to describe only parts of the system [10,6], and Milbergs and Vonortas [5] “conclude that the currently available indicators and measurement methods do not adequately describe in a timely manner the dynamics of innovation today.” Even the Oslo Manual, which is the European major approach to innovation indicators, recognizes the need for new indicators [11]. The mainstream in research on innovation generally focuses on the innovation process inside the firm [12], also concentrating on its relation to economic growth on national levels [8]. Additionally, innovation actors have traditionally been viewed as separate and unique from the resources and contexts within which they are embedded [13].
We subscribe to Still et al. [6] in that it is time to start using the vast new data sources related to innovation activities and, moreover, to echo the real-time nature of the data in the ways it is used to measure or rather monitor innovation. With this paper, we want to build on and extend the foundational work on data-driven innovation ecosystem investigations by Rubens et al. [14], Still et al. [15], Russell et al. [16], and Basole et al. [17] by investigating whether the data-driven network analysis of the structure of an innovation ecosystem can be used to reproduce the results of a traditional innovation measurement approach, here Innovation Union Scorecard. In addition to comparing the results of the two approaches, we explore the ways that data-driven visual network analysis can be used to support decision making in the context of innovation ecosystems beyond what is made possible by traditional means to measure innovation. The applied approach to measure innovation emphasizes relationships that serve as conduits for information, talent and financial resources [18]. This paper is, to our knowledge, the first to compare the results of network analysis of socially constructed data to traditional innovation indicators, here Innovation Union Scoreboard. Through four cases, each representing a different Performance Group, we investigate how the new indicators reflect the traditional indicators. We create, analyze and visualize network representations for the four case nations. Finland represents Innovation leaders, Estonia Innovation followers, Hungary Moderate Innovators, and Latvia Modest innovators.

1.1. Innovation ecosystems

It has been widely acknowledged that innovation activities are rarely carried out within a single organization. Rather, the needed knowledge and other resources are oftentimes extracted from multiple sources. For example, Triple Helix Model has looked at university-industry-government relations [19]; competitive advantages are seen to build from the linkages between activities [20]; open innovation has concentrated on sources of innovation beyond one individual entity [21], and co-creation in complex networked world has included other stakeholders such as customers to the picture [22]. Furthermore, context of value creation has been seen to be networks [23,24].

Overall, the networked approach to innovation has been recognized. The fundamental idea is that individuals and organizations do not operate merely in dyadic relationships, but rather that they are deeply embedded in complex economic and social systems consisting on numerous inter- and intraorganizational relationships [25,26]. Accordingly, word ‘ecosystem’ has been introduced as the inter-organizational, political, economic, environmental and technological systems of innovation through which a milieu conducive to business growth is catalysed, sustained and supported [18]; and service ecosystem referring to “a spontaneously sensing and responding spatial and temporal structure of largely loosely coupled value proposing social and economic actors” [13].

1.2. Investigating innovation ecosystems as networks

Networked innovation has increasingly been viewed and studied as a complex system. For example, Basole et al. [26] have studied value creation in complex enterprise networks. Katz and Cothey [27] took up the challenge to start building a bridge between the Web and complex innovation systems and presented a set of web indicators for complex innovation systems, essentially focusing on the topology network of interlinked web pages related to different innovation systems. Ferrery and Granovetter [12] have analysed the role of venture capital firms in Silicon Valley’s complex innovation network using complex network theory, a perspective that looks at multiple interactions between numerous and diverse agents characterized by the non-linearity of their interactivities [28,29].

Even though there are various ways and levels to model an innovation ecosystem as a network, it has been accepted that no single modeling method is able to cover a complex system as a whole. The modelling may include actors such as companies (both established and start-ups, or growth companies), enterprises, firms, venture capitalists (VCs), angel investors, universities, policy makers, research institutes, banks [13]; connected through alliance agreements, shared ventures or other kinds of strategic collaboration; through financial flows such as investments; through shared platforms, acquirements or even law suits; on micro, meso and macro levels [13,30].

We believe that in order to show the big picture of an innovation ecosystem, making visible the meaningful entities of the system and their interconnections is the starting point. Network analysis enables this. The method of social network analysis (SNA) studies the structure of networks as social actors [31], and has been used for decades to study the sociological relationships of people and organizations [32,33]. Precise quantitative SNA metrics can be calculated for both a network as a whole and for its actors. Whereas simple metrics such
as nodal degree (representing the number of connections of a node) are a good starting point to support visual network analysis, more complex metrics such as betweenness centrality, prestige \([32]\), page rank \([33]\), and measures of hubs and authority \([34]\) have their role in the quantitative analysis process.

Network analysis affords insights into the social configurations of the network representing and making explicit the links (relationships) connecting actors, or nodes (social system members), and network visualizations assist in enabling to see the context of network and furthermore, communicating findings to others \([13,36]\).

1.3. Web and social media data

From data availability viewpoint, two important phenomena stand out: Web 2.0 and social media, such as Twitter, blogs, socially constructed data (referring to entities created Wikipedia-style), Facebook, LinkedIn and others.

The concepts of open data, linked data are adding to the continuously expanding set of digital data on all the different aspects of human life where the problem is no longer the availability of the data but the humongous volume of both real-time and historic data that makes the management and processing of the data a complex task (http://www.economist.com/node/15557443).

Everything that is publicly available online can be used as a source of data and in many cases the data is available in a machine-readable format. Coupled with modern computing power, Web APIs (application programming interfaces) and scrapers allowing the programmatic access to online data, utilizing this data through automated, sophisticated processes provides possibilities for serendipitous reuse and mashup development \([37]\).

Here, we tap into Innovation Ecosystems Network Dataset (IEND) \([14]\), a socially constructed and curated (or crowd-sourced) rich data about companies at the meso- and micro-levels, as well as individuals and investors related to them in almost real-time, though with baked in bias toward activities that are of interest to a larger audience and therefore get added to different databases.

The socially constructed dataset is built by crawling the World Wide Web for socially curated information on press-worthy technology-based companies, their affiliations to executives, advisors, board level personnel, and investment organizations. Moreover, the dataset includes acquisition information providing links in between the companies. Rubens et al. \([14]\) describe the dataset and the process used for collecting it in detail. The dataset includes around 90,000 companies, 100,000 individuals, and 6,000 investors for the time period used in the analysis, i.e. year 2012 and before. The connections between entities are established (1) through financial activities (investor invests in a company), also acting as surrogate for other types of resources that are being exchanged, and (2) through employment (individual is connected to the company in which he/she has worked for or is currently working).

Traditional company data sources tend to have data about the established, larger companies; start-ups and growth companies are oftentimes missing from that data \([17]\). One of the strengths of the applied approach is that socially constructed data includes start-ups or growth companies. They are a major source of new innovations, and are built around individual people—whose data is not available from traditional innovation sources—and their resources: company founders and co-founders, core team members, board members, advisors, business angels providing both early funding as well as their knowledge and, importantly, connections; some of these have been addressed by exploring the role of venture capital firms \([12]\).

Again, it is important to note that the dataset inherits both the advantages and disadvantages of socially constructed data. Some of the advantages are availability, large coverage, timeliness, community verification of the data, and that the raw data is oftentimes “free of cost”. Some of the disadvantages are potentially erroneous data and the bias of the individuals, as well as the fact that it might be neither statistically representative nor complete as such.

2. Analyzing the context of innovation system in Europe

Toward understanding the complexity of innovation better, we have have put together a process and a supporting set of tools for accessing IEND data and for analyzing and visualizing the innovation ecosystems under investigation as networks. In this study, we will be explaining the value of our approach in the context of Europe.

2.1. The Innovation Union Scoreboard

The Innovation Union Scoreboard measures the innovation performance at large in the European Union, with a framework consisting of weight innovation dimensions and 25 indicators. It provides a comparative assessment of the research and
innovation performance of the EU Member States and the relative strengths and weaknesses of their research and innovation systems. It helps Member States assess areas in which they need to concentrate their efforts in order to boost their innovation performance.


The Innovation Union Scoreboard 2015, the 14th edition since the introduction of the European Innovation Scoreboard in 2001, follows the methodology of previous editions. Innovation performance is measured using a composite indicator—the Summary Innovation Index—which summarizes the performance of a range of different indicators. The Innovation Union Scoreboard distinguishes between 3 main types of indicators—Enablers, Firm activities and Outputs—and 8 innovation dimensions, capturing in total 25 indicators. The measurement framework is presented in Figure 1.

![Figure 1. Innovation Union Scoreboard framework](image)

The Innovation Union Scoreboard uses the most recent statistics from Eurostat and other internationally recognised sources such as the OECD and the United Nations as available at the time of analysis with the cut-off day by the end of November 2014. International sources have been used wherever possible in order to improve comparability between countries.

2.2. Process for investigating the European Innovation Ecosystem

Previous studies taking a data-driven network analysis and visualization approach into innovation ecosystem analysis include exploring the networks of companies and investors of selected university alumni [38], the mobility of individuals in the context of European innovation ecosystem [15] and the patterns of co-creation within a national innovation ecosystem [39]. Figure 2 shows the data-driven process for investigating the network structure of innovation ecosystems.

![Figure 2. Data-driven approach for exploring innovation ecosystem structure](image)

As the Innovation Union Scoreboard 2011 presents typology of innovation related performance, we want to complement them by exploring the related networks and their characteristics. Are their network analytics different? Do they look different? As the report does not include network analytics or network visualizations of the innovation systems it is targeting, we now proceed to explore these. We have selected examples of each of the four groups for our analysis: Finland represents Innovation leaders, Estonia Innovation followers, Hungary Moderate innovators and Latvia Modest innovators.

4. Findings

Table 1 shows the details of the investment rounds for the four countries. Finnish companies have collected a total of more than 200M dollars of venture capital investments in more than hundred rounds. Innovation follower Estonia is second in the number of investment but the total amount of investments in Hungary is larger to Estonia. According to the data, Latvian companies have received only a few seed-level investments.

<table>
<thead>
<tr>
<th>Country</th>
<th>Rounds</th>
<th>Investments</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finland</td>
<td>109</td>
<td>175</td>
<td>$223M</td>
</tr>
<tr>
<td>Estonia</td>
<td>22</td>
<td>25</td>
<td>$6M</td>
</tr>
<tr>
<td>Hungary</td>
<td>19</td>
<td>18</td>
<td>$26M</td>
</tr>
</tbody>
</table>

Table 1. Investment rounds in the sample
Figure 3 shows the development of investments that companies in the four countries over time. For contrast, we note that the other European innovation leaders have collected even more investments than Finland: Germany a total of $1,998,958,000, Denmark $505,024,000, and Sweden $805,153,000.

When compared to the statistics collected by the Finnish Venture Capital Association (http://www.fvca.fi/en/knowledge_centre/statistics/), we see that our dataset captures roughly 8-15 per cent of the total amount of investments in Finland. While we do not have similar data for the other countries for comparison, we expect that the with the global nature of the data source and the data-driven nature of the approach, our sample for the other three countries is similar to Finland. The margins are quite large, however, thus we acknowledge that from pure numbers viewpoint, social media originated data does not allow conclusive results.

As our primary object is to study the structure of the whole of ecosystem, we focus on the entity of a network that companies, related individuals and investors form. Still, for the better explaining power, especially toward the qualitative narrative of the results, the metrics include both node level and network level measures [16].

4.1. Network visualization

A network representation not only shows the size of the ecosystem as a whole but it also reveals its structure and the roles and importance of individual actors. Figures 4, 5, 6 and 7 include network views for the four ecosystems. Dark red nodes represent companies that have received an investment in the last 12 months; the other companies are pink. Dark green nodes are investors that have been active in the last 12 months; the other investors are light green. Blue nodes represent individuals. By highlighting the nodes with most recent activity, we are able to support the investigator in focusing into areas in the ecosystem where actors are making moves.

To indicate the role of an individual actor in the network, nodes sizes are set proportional to their betweenness centrality. From network topology viewpoint, betweenness centrality is the number of times when a particular node is included in the shortest path between any two nodes in the network [26]. Betweenness value indicates that a node has a significant connecting or bridging role in the network. With the kind of modeling used here, nodes representing individual investors and people tying together cluster in the network are highlighted.

A visual investigation of the four networks shows that the networks are different from each other. The network for Finland is both the largest and also the most connected one. A single venture capital investor, Finnish Industry Investment, is the most prominent one. Two of the individuals have a very significant connecting role in the network. Many of the recent investments are for companies that, according to our data, are not connected to the core of the network. We see that as a positive sign; the ecosystem is not dependent on a single investor or a small hub of investors.

We are aware that our approach does not cover the whole of the ecosystem. Nokia, one of the key players in Finnish high tech innovation, for example, is present in the network but does not seem have a significant role: Nokia has neither received nor made investments recently, thus a pink node, but many of the individuals founding or co-founding companies do have a connection to Nokia.

Sportlyzer in the most prominent node in the Estonian network. Two clusters of companies exist but, according to the data, are not connected to each other. There are only a few investors visible in the network. Companies that are existing growing even without help from investors show the potential of the ecosystem. In the Hungarian network, an individual company has an even more dominant role in the network: Prezi is attracting both the general public as well as investors with their cloud-based service for zoomable presentations. The companies in the Latvian ecosystem do not have major connectors between them. Companies such as Wheemplay and Ask.fm are recognized internationally.

4.2. Network metrics

To create a quantitative footprint or a signature for the four networks, we further calculate a number
of network-level metrics following Russell et al. [16]. As snapshots their explaining power is limited; however, in comparisons as well as in longitudinal studies they are seen to provide better insights for decision-making [18]. Hence, we see that they are applicable to our research context of comparison of 4 European country ecosystems. Includes a collection of key network level metrics for the four ecosystems. The Finnish ecosystem is composed of 826 nodes, Estonian of 199 nodes, Hungarian 170 nodes and Latvian of 72 nodes. The number of investments for Finland, representing Innovation leaders in this investigation, is the key distinctive measure. The number of companies, the number of investors and the number of individual people in the network representing the Finnish innovation ecosystem are much larger compared to the other three countries.

Table 3 presents a series of actor-level metrics. The investors in the Finnish innovation ecosystem have, in average, more connections to different companies, 1.99 for Finland (compared to 1.6, 1.25, 1). This is largely due to Finnish Industry Investment’s degree value: it has invested into 22 companies according to the data.

There are no major differences in the average degree value for individuals. An individual with a degree of 7 in the Finnish innovation ecosystem stands out. For an individual, large degree value indicates either mobility or the role of serial entrepreneur or business angel.

Importantly, the order of the countries follows that of EU Innovation Union Scoreboard Performance groups.
**Figure 7. Innovation leader: Finnish innovation ecosystem**

**Table 2. Network-level metrics**

<table>
<thead>
<tr>
<th>Performance Group</th>
<th>Nodes</th>
<th>Edges</th>
<th>Nodes in largest component (relative)</th>
<th>Component s</th>
<th>Mean degree</th>
<th>Max degree</th>
<th>Mean betweenness</th>
<th>Max betweenness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finland</td>
<td>826</td>
<td>652</td>
<td>310 (36%)</td>
<td>204</td>
<td>1.58</td>
<td>39</td>
<td>0.001</td>
<td>0.084</td>
</tr>
<tr>
<td>Estonia</td>
<td>199</td>
<td>155</td>
<td>53 (26%)</td>
<td>48</td>
<td>1.56</td>
<td>14</td>
<td>0.002</td>
<td>0.050</td>
</tr>
<tr>
<td>Hungary</td>
<td>170</td>
<td>124</td>
<td>30 (18%)</td>
<td>47</td>
<td>1.46</td>
<td>29</td>
<td>0.000</td>
<td>0.029</td>
</tr>
<tr>
<td>Latvia</td>
<td>72</td>
<td>41</td>
<td>6 (8%)</td>
<td>31</td>
<td>1.14</td>
<td>5</td>
<td>0.000</td>
<td>0.004</td>
</tr>
</tbody>
</table>
Table 3. Actor-level metrics

| Country | Companies |  | Investors |  | Individuals |  |
|---------|-----------|  |-----------|  |-------------|  |
|         | Count     | Mean | Max       | Count     | Mean | Max       | Count     | Mean | Max       |
| Finland | 305       | 2.15 | 39        | 69        | 1.99 | 22        | 452       | 1.13 | 7         |
| Estonia | 71        | 2.23 | 14        | 10        | 1.6  | 5         | 118       | 1.15 | 3         |
| Hungary | 53        | 2.38 | 29        | 8         | 1.25 | 2         | 109       | 1.03 | 2         |
| Latvia  | 35        | 1.23 | 5         | 2         | 1    | 1         | 35        | 1.06 | 2         |

7. Discussion

In this paper, we explored the possible contributions of novel innovation indicators based on social network analysis in the context of complex innovation networks. We investigated whether the data-driven network analysis of the ecosystem structure using SNA can be used to reproduce the results of a traditional innovation measurement approach, more specifically Innovation Union Scorecard, which is a leading composite indicator used in Europe. Hence, we explored the explaining power of SNA metrics and supporting decision-making in the context of innovation ecosystems.

We conducted our analysis among four European countries, using the traditional indicators of Innovation Union Scorecard 2011 and their characterization of countries into Innovation leaders, Innovation followers, Moderate innovators, and Modest innovators. Taking a data-driven network analytics approach and using socially constructed data, we were able to reproduce the order of the four countries as per their Innovation Union Scoreboard Performance Groups. For example, network metrics of Finland, described as an Innovation leader, are higher than those of Latvia, a modest innovator.

The applied approach to describe the characteristics using data-driven network analytics provided interesting results in forms of actor and network-level metrics and network visualizations. These novel innovation indicators are not intended to replace the existing ones, but to complement and validate the existing innovation indicators.

The applied approach introduces completely new means to support decision-making. Visualizations enable exploration, identification, discovery, and communication of complexities that previously have been ignored [26]: (1) Visualization enables decision and policy makers to analyze and understand the structure of complex systems, identify roles that actors play, and the potential evolution; (2) Mapping actor relationships enables researcher and decision makers to understand and identify patterns and structures of actors engaged in innovation and value creation, (3) providing a platform to differentiate complex network systems by purpose, in terms of the ways firms compete and collaborate; and (4) enables one to explicitly map actors in the decision space, as it possible to see how actors relate to each other.

We see that a network visualization of an innovation ecosystem is of most value when used as a medium for visual storytelling for supporting the search for a shared vision between the different actors and stakeholders of the ecosystem. This has been eloquently expressed as “The transformative potential of the shared vision for an innovation ecosystem arises from new coalitions and network connections and the relationships on which they are based. Their shared vision is collectively realized and continually updated by the co-creation of events and their impact. The transformative potential of an innovation ecosystem lies in its capacity for continual realignment of synergistic relationships of people, knowledge and resources that promote harmonious growth of the system in agile responsiveness to changing internal and external forces.” [18]

An obvious problem of a traditional statistical indicator is its limitations for action. For example, if the amount of investments has increased, it is great news for the other companies involved in an ecosystem. However, the information alone does not allow a discussions on how the other actors in an ecosystem can take into account the increased flow of venture capital in their own operations or in which part of the ecosystem the flow has increased, specifically.
Taking the presented approach for analyzing an innovation ecosystem, policy-makers and other decision-makers are able to take a system-level view into the structure of the innovation ecosystem. Moreover, visualization supports discussions with a shared point of reference. Different network metrics can be used to highlight actors taking different structural roles. Financial or innovation performance can also be projected into the network view for context and overview. In addition, actor-level network metrics can be analyzed against other innovation metrics for insights on how structural position in innovation ecosystem may be associated with their innovation performance.

Social media has afforded more or less any Web user the role of contributor or content publisher. Therefore, they have highlighted the role of individual in co-creative innovation activities as individuals have many opportunities for creating, communicating and collecting information and knowledge related to the innovation outputs as well as the process of innovation [40]. The benefits and necessity of user involvement and their integration to innovation is widely acknowledged, as users are seen as source of inspiration that can foster innovation in its own right [41]. Moving away from producer innovation toward open single user innovation and open collaborative innovation is encouraged to provide economic viability of innovations [42].

Social media analytics already seeks to provide insight for the different players in social media for the different aspects, oftentimes concentration on marketing and advertising research. A related set of indicators falls roughly to categories: Community, Traffic, Conversations and Engagement, Leads, and Conversions (http://socialmediasonar.com/five-social-media-key-performance-indicators). More specifically, a social media analyst is interested on the nature and structure of the community of people relating to a brand, enterprise or other entities in social media. Further, the analyst is interested in the behaviour of the actors.

We do realize that social media data does not cover everything related to innovation, as activities in different levels are not communicated or recorded by social media. Nevertheless, we see that Web 2.0, social media user generated content, as well as the indicators used to measure social media all contribute to the development of new indicators for monitoring innovation-related activities surfacing in social media, thus supporting understanding innovation ecosystems.

We seek to continue our work to move these visually represented analytics into use in innovation ecosystems of various kinds. Further, we continue to introducing additional sources of data to the analysis to better capture the different aspects meaningful in better understanding the structure and dynamics of innovation ecosystems and thus innovation as such.

8. References


