

Evaluating Efficiency of Collective Learning in Innovation Networks: Simulation based Experiments in SKIN

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Abstract

Background/Objectives: Innovation networks aim to increase collective learning and are a means of creating innovation. Different policies are made to increase the efficiency of these networks. These policies have several financial consequences for policy-makers. One of the most low-cost policies is a policy to increase collaborations and communications among network members, which leads to the improvement of collective learning and network efficiency. **Methods:** The present paper aimed to study the effect of increased network collaboration and communication on network efficiency through experiments based on simulations in the SKIN framework. In addition, the effect of density, as the notion of network complexity, is also examined in this regard. The analysis performed on simulated data using the structural equations method. **Results:** The results of simulation and structural equation modeling revealed that density is a variable with mediating and moderating effect on the relationship between support for collaboration and network efficiency. **Application:** The results of this research could be used by policy makers who want to use support for collaboration a policy to improve network efficiency. Although the increase in collaboration could increase efficiency but the more increase in it could increase network complexity and though decrease network efficiency.

Keywords: Collective Learning, Complexity Catastrophe, Innovation Networks, SKIN Framework

1. Introduction

Study of the emergence and dispersion of innovation was for the first time discussed by Joseph Schumpeter in 1912, in economic discussions. He emphasized on the prominent role which an entrepreneur plays in economy¹. About 30 years later, in 1942, Schumpeter introduced the growth of the American industry as the result of changes made to the structure of the research and development process through establishment of specialized laboratories by big companies. About 40 years later, another change was made in the structure of research and development structure of big companies. The change led to establishment of an interaction between research and development laboratories and other actors such as universities and public

research institutions within the framework of innovation networks¹. However, analysis of these networks and their effect on economy has been theoretically studied since 1990s. Pyka and Fagiolo² believe that one of the reasons for the delay in theoretical analysis of innovation networks is problems caused by the Firm Theory (in the form of neoclassical economics and industrial organization) to the economics.

The recent approach to innovation networks –which supposes networks as a means of innovation- realizes that, the main advantage of networks is creation of innovation opportunities for different firms. It also introduces networks as a social process including interactions, coalitions and collaborations among various actors. That is to say, the firms use inter-organization networks as safe platforms

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which protect them against unreliability and unfavorable business conditions. Since interactions among network members (network density) and collaborations among them are considered as a means of innovation, apparently with an increase in the number of interactions among members, collective learning and network efficiency are enhanced. Hence, the present paper aimed to answer the following questions: What is the effect of a support for collaboration aimed at creating a chance for collective learning on network efficiency? What is the effect of complexity catastrophe (increased network density) on the relationship between support for collaboration and efficiency?

2. Literature Review

Networks were considered as a means of innovation more than before with the emergence of Nelson and Winter's evolutionary economics³. Moreover, more studies were conducted on these networks in the form of dynamic systems and especially complex adaptive systems^{4,7}. The complex adaptive systems were formed following the criticisms on system thinking about self-organization and co-evolution and have the following characteristics^{8,9}

- They are formed of a set of components with numerous communications among them.
- Instead of modeling complex and nonlinear systems, they study the interactions among components (agents) using a set of variables and causal relationships.

2.1 Learning in Complex Adaptive Systems

Most learning theories refer to the existence of a relationship between agents and the outer environment that influence their knowledge acquisition capabilities. However, these theories have never explored this relationship seriously. These theories only emphasize on single-agent learning and do not address interactive learning. Researchers of collective learning believe that the act of learning not only takes place in the person's mind, but also can take place at the social level where individuals connect⁹.

Lave and Wagner¹⁰ introduced this type of learning as situated learning. In this type of learning, focus is moved from people's mentalities to the relationships among their mentalities and also the focus on individuals' characteristics or their environments is replaced by the focus on inter-person interactions or interactions among people and the environment. According to them, situated learning has the following two major characteristics:

- Individual learning is not separable from collective learning
- Learning is modeled in the form of organizational communications forming a learning network

2.2 Collective Learning and Kauffman's Complexity Catastrophe

Yuan and McKelvey⁹ used the NK modeling concept, which was proposed by Kauffman¹¹ to simulate the efficiency of complex systems, to test the efficiency of collective learning. Kauffman believed that an increase in the number of communications among interacting agents leaves a nonlinear effect on their relationships and finally leads to complexity catastrophe (Figure 1). His use of the phrase "complexity catastrophe" was aimed at showing the fact that an increase in social interactions first facilitates learning. Yuan and McKelvey⁹ used the NK modeling method to test different hypotheses on the rate of collective learning as well as the degree of collective learning. They showed the number of group members with N and the number of communication with K . The most important hypotheses tested by these researchers through simulation are as follows:

- For small values of K the rate of collective learning is a positive function of communications among members (K).
- For high levels of network density accelerates learning, but it easily is entrapped by low-level learning.
- As K reaches $N-1$ value (and for very large values of N), adaptive learning is lost. (the Complexity Catastrophe)

On the other hand, McKelvey¹² believes that collective learning is an integral part of today's competitive world while complexity of communications may balance the success of firms or the network competitive advantage. He also believes that there is a very small difference between Kauffman's complexity concept and network density. Therefore, he explored answers to the following three questions:



Figure 1. Increasing Complexity of system by increasing K .

- Does the existence of many co-evolution relationships among competencies of the value chain of a firm hinder competitive advantage?
- Does the existence of many co-evolution relationships among one firm and another hinder competitive advantage?
- Do strategists need to be worried about the complexity catastrophe?

2.3 Analyzing the Dynamics of Complex Adaptive Systems

Anderson⁸, Yuan and McKelvey⁹, Stacey et al.¹³ and Mahmoudzadeh and Jassbi¹⁴ stated that the best method of modeling complex adaptive systems is the agent-based modeling method. In the agent-based modeling method a whole system is modeled in the form of a set of independent decision-making components known as an agent. This method is used to model individuals' behavior and their relationships. Moreover, unlike the previous methods it can also model the heterogeneity among components. The three main characteristics introduced for this method are as follows¹⁵:

- The ability to analyze the emergent phenomenon in systems.
- Providing a more natural system model compared to other methods.
- High flexibility.

2.4 Simulation of Knowledge Dynamics in Innovation Networks

Various studies have been conducted on modeling the dynamics of innovation networks using the agent-based modeling method. However, one of the most commonly used studies¹⁶⁻¹⁹ is the framework proposed by Ahrweiler et. al⁴ in a study titled "Simulation of Knowledge Dynamics in Innovation Networks" (SKIN). This framework is an agent-based computer simulation which studies dynamic processes associated with innovation in knowledge-based industries.

The SKIN model is an agent-based model composed of heterogeneous agents interacting in a variable and complex environment. Agents of innovative firms try to sell their innovations to other agents and the end users. Each firm tries to enhance its efficiency with regard to innovativeness by improving its knowledge base through one of the three following methods: adapting to the needs

of the end user; incremental or radical research; and collaborating with other firms (or creating a collaborative network). In the SKIN model a Kene is used to show the total knowledge of an organization. The knowledge base of an agent in the SKIN model includes a set of knowledge units. Each unit of knowledge is expressed as a (C, A, E) triple, which C denotes the scientific or technical Capability of a firm in a business area (e.g. biochemical engineering), which is shown by an integer. A is the Ability of a firm to perform a task in the field of concern and is shown by a real number. Examples of this ability include a mixing or filtering method. Finally, E stands for the Expertise level achieved by the firm in doing the aforementioned ability. E is shown by an integer. The Kene for each firm is a set of knowledge units' triple whose count depends on the firm size (Figure 2).

Innovation Hypothesis (IH) is the concentration of firms on a specific field and innovation in that field. In other words, it is the potential innovativeness of the firms. The innovation hypothesis is, in fact, a set of Kene triple of a firm (Figure 3).

Transformation of IH to a product is a process that multiplies the capabilities and abilities of the IH to calculate an index for the product (Equation 1).

$$P = \left(\sum_{IH} C_i, A_i \right) \text{ mod } N \tag{1}$$

3. Research Model

Figure 4 shows the research model in the form of path analysis diagram, which by Partial Least Squares Structural Equation Modeling (PLS-ESM) techniques (using Smart PLS) will be tested. In this model the effect of different levels of "support of collaboration policy" (independent variable) on efficiency of network (dependent variable) will be tested. Also in this model the effect of complexity

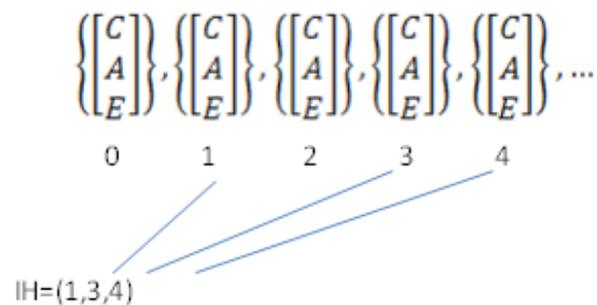


Figure 2. Kene of a firm.

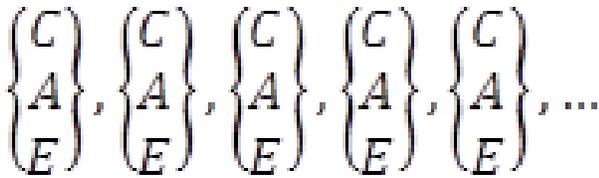


Figure 3. Innovation Hypothesis.

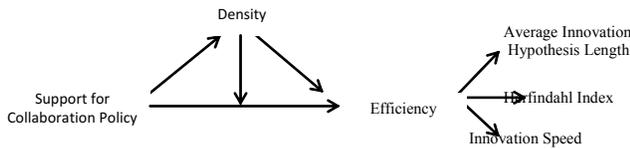


Figure 4. Research Model.

Table 1. Relationship between SKIN Framework and research model variables

Variable Type	Variables in Research Model	Equivalent parameter/output variable in SKIN
Dependent / Latent	Efficiency of Network	Herfindahl Index
		Avg. Innovation Hypothesis
		Speed of Innovation
Moderator / Mediator	Complexity	Network Density
Independent	Support of collaboration policy	0.7
		0.3
		0.1

of network as a moderator/mediator variable on this relation will be tested.

The data needed to test this model have been produced by the SKIN framework which is simulation of artificial innovation networks. Table 1 shows the relationship between SKIN framework’s parameters and outputs by the variables of research model (Figure 4).

3.1 Efficiency

Is a latent variable which has been defined by the following variables:

3.2.1 Herfindahl Index

This index is used to measure firm size (the firm capital and the size of its IH) in relation to the whole industry. It is also an index that shows the competition between the firm

and the industry (whether monopolized or competitive). This index can also be compared to a set of specific values and monitor its variations over time. In this research, the second approach was used.

3.2.2 Average Innovation Hypothesis (IH)

The length of the IH of each firm shows the ability of the firm to produce diverse products. In other words, as the number of abilities in a network increases, the possibility to produce more products grows as well. This variable reflects the level of technological development in the network and was used to measure the technology index of the problem.

3.2.3 Speed of Innovation

The shorter the interval between productions of two successful products, the higher is the innovation speed. This index is a criterion for measuring the gap between science and product productions. Hence, this variable is used to measure market index.

3.2.4 Complexity

Complexity is a research variable which has been showed by the network density in simulation.

3.2.5 Support of Collaboration Policy

The policy to support member collaboration is, in fact, an incentive to increase collaborations among firms or to reinforce their mutual trusts. The policy to support collaboration is independent variable which is a categorical variable with three values: more support, relative support, lack of support which is controlled in SKIN by the Attractiveness-threshold parameter at three levels: 0.1, 0.3 and 0.7 respectively.

4. Results

After running the SKIN program for three levels of the Attractiveness-threshold parameter, variations of network density were obtained as seen in Figure 5. According to this Figure, with an increase in the support for collaboration (or a reduction in attractiveness-threshold), network density increases.

In order to test the model using the structural equations method smartPLS software has been used.

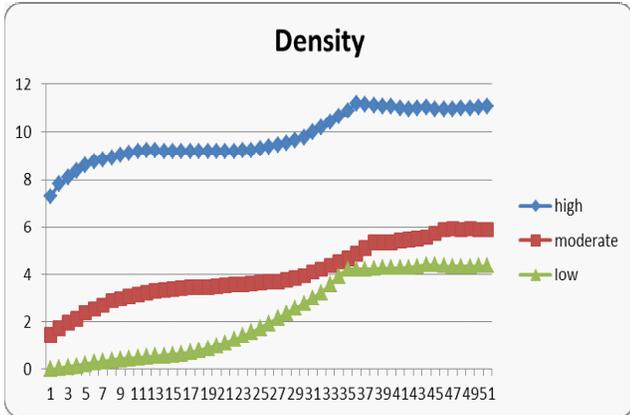


Figure 5. Network density for different levels of collaboration.

Based on Kwong and Wong²⁰ the results of model analysis are as follows:

4.1 Explanation of Target Endogenous Variable Variance

Figure 6 shows the path modeling in smart PLS. Numbers in the circle show how much the variance of latent variables is explained by the other (coefficient of determination, R^2) latent variables which in this case R^2 is 0.694 for the efficiency endogenous latent variable, which means that the three variables (Policy, Density and Policy*Density) moderately explain 69.4% of the variance in efficiency. Also Policy explains 66.3% of the variance of Density.

4.2 Inner-Model Path Coefficient Sizes and Significance

In Figure 6 numbers on the arrows are called the path coefficients. They explain how strong the effect of one variable is on another variable. The weights of different path coefficients enable us to rank relative statistical importance. So Figure 6 shows that density has the strongest effect on efficiency (-0.917) followed by policy (-0.779) and policy*density (-0.406). The hypothesized path relationships between policy, density and policy*density on efficiency are statistically significant because all of the absolute values (0.779, 0.406, 0.917) are greater than 0.1 (Figure 6.) and all of the T-statistics (6.663, 7.203, 6.492) are larger than 1.96 (Figure 7).

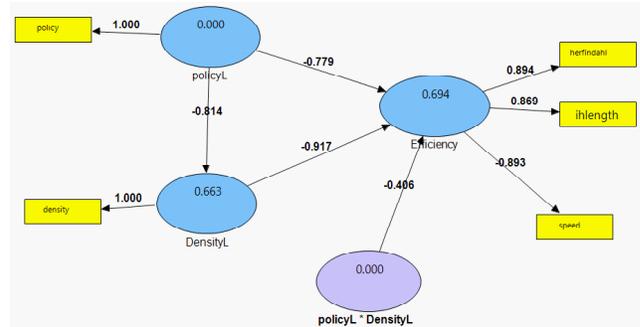


Figure 6. Moderating and mediating effect of density on network efficiency.

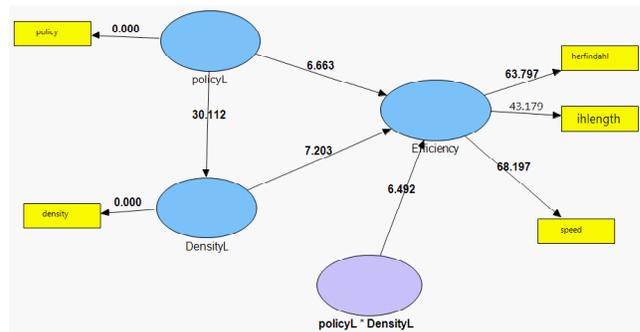


Figure 7 Model significance.

4.3 Outer Model Loading

Outer model loadings show the correlation between latent variable and the indicators in its outer model. Figure 6 shows these indicators (Innovation Hypothesis, Herfindahl Index, Speed of Innovation) for efficiency latent variable, which their loadings are 0.869, 0.894 and -0.893.

For these values the absolute value of 0.7 or higher is preferred, but in exploratory researches 0.4 or higher is acceptable.

5. Conclusion

Results of the experiments based on simulation using the SKIN framework indicate that with an increase in communications within innovation networks, network efficiency, which is caused by collective learning, increases. However, increase in density has a negative effect on efficiency. This complies with findings of Kauffman¹¹ and McKelvey¹² that reflected the moderating effect of complexity (density) on efficiency. Moreover, the results of this paper show that density also influences the relationship

as the mediating variable. Policy makers in the field of innovation networks should note that although support for collaboration among members increases efficiency, but this policy should be used together with other supportive policies such support of startups, since using only this policy and increasing support of collaboration will reduce the efficiency.

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