The sociological theory of Crozier and Friedberg on organized action seen through a simulation model

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Abstract

The paper shows certain dynamics aspects of competition among firms, particularly in the biotechnology sector, using innovation networks in accordance with the sociological theory of organized action of Michel Crozier and Erhard Friedberg. Firstly it provides an overview of relevant literature on innovation and biotechnology firms. It also reviews briefly the mentioned theory which is represented in a simple system dynamics simulation model. The sociological concepts of *actor*, *game*, and *system*, are examined through the lenses of the model. Basically, the model provides a ground in order to discuss, develop and test particular theoretical statements of Crozier and Friedberg and the implications of their assumptions that are not intuitively obvious. The match between these two different approaches shows a way to bridge scientific disciplines that maybe are not far away one from each other.

Key words: Crozier, Friedberg, system dynamics, Innovation networks, sociology.

1. Innovation networks and biotechnology firms

The broad distribution of knowledge (the source of competitive advantage) that generates the need for firms to engage in interorganizational relationships (Powell, Koput & Smith-Doerr 1996) as well as the *systemic*[1] character of current technological solutions (Küppers & Pyka 2002) are among the reasons for the rise of innovation networks. In this sense, an innovation network can be seen as interaction processes between a set of heterogeneous actors producing innovation at all possible levels of aggregation (Küppers & Pyka 2002). However, there are still multiple questions to consider within this scintillating research area: Why do organizations form innovation networks? How are they organized? How can we analyze innovation processes in networks? What is the structure of an innovation network? What co-ordination mechanisms are important and what dynamics emerge from interactions? (OECD 2000; Birkinshaw 2002; Hansen 2002;

[1] The word *systemic* refers to the complex net of relationships in a system that demands an approach that considers the emergent properties that arise due to these interconnections. Complexity Theory and Systems Thinking are wide fields that have, for more than half a century, been dedicated to developing these topics. A general overview can be found, for example, in the works of Bar-Yam (1997) and Flood (1993).

Küppers & Pyka 2002). This paper will focus on the dynamics of innovation networks in order to indicate a way to analyze their role in competitive environments such as biotechnology.

The biotechnology sectors (e.g., pharmaceutical, food, environment etc.) are an innovative industry with high investment risks (Oliver & Liebeskind 1998; Baum, Calabrese & Silverman 2000) and a complex, expanded and dispersed knowledge base (Powell, Koput, Smith-Doerr 1996). In such a knowledge-intensive industry it can be assumed that knowledge is created and utilized in an interactive way during which interorganizational networks could be appropriate - as Küppers & Pyka (2002) suggest - in order to acquire relevant resources (like scientific and management know-how). These networks need to be developed and change over a life cycle because a single biotechnology company cannot assemble all required skills. Moreover, the purpose of interorganizational collaboration changes over time corresponding to the particular challenges a firm faces. At the early stages biotechnology firms' (BFs) technical and scientific networks with research institutes or universities will dominate, followed by alliances to acquire capital, to conduct clinical trials or to secure federal regulatory approval. Finally, new relationships have to emerge for production, commercialization and distribution purposes (Powell, Koput & Smith-Doerr 1996; Powell et al. 1999).

Maurer (2001, 2003) has recently done in-depth research on the dynamics of why and how firms enter into collaborative arrangements and on the most successful way of collaborating. Applying the construct of social capital[2], she identified three development phases for new biotechnology firms (NBFs) in Germany: NBFs normally start as "sheltered scientific workgroups" in which they have contact with universities and research institutes in a so-called knowledge network. In a second transformation phase, successful NBFs start a continuous juggling act in order to gradually acquire the needed resources, e.g., administrative, political, and customer capital, whereas unsuccessful NBFs try to quickly transform their network to meet the changing environmental demands and finally fail. Successful NBFs build and keep weak and strong ties to the different networks and finally reach the state of so-called "virtually integrated NBFs". Unsuccessful ones drop back to the stage of "sheltered scientific workgroups" (see figure 1 in the appendix). Anderson, McNiven and Rose's (2002) analysis of patterns of collaboration in Canadian BFs arrived at similar results. First of all they found that the more collaborative arrangements BFs enter into, the more successful they are at raising capital. They additionally found that small firms mainly enter into collaborations with large firms to gain access to capital, markets and distribution channels as well as to protect intellectual property. Conversely, large firms preferably collaborate with small firms for purposes of prototype development, accessing knowledge and R&D. As far as the life cycle is concerned, BFs collaborate with universities and research facilities in their early stages. Later access to knowledge on regulatory affairs, capital and distribution channels dominates (Anderson et al. 2002).

To summarize, BFs establish different networks that fit their changing internal and external demands. Koput, Smith-Doerr & Powell call these characteristics "a path-dependent 'cycle of learning'" (1997: 230) where early collaboration leads to more centrality. In a nutshell, this innovation networks become self-organising structures that reduce the complex dynamics of innovation processes, as suggested by Küppers (2002). How can the dynamics of these networks be addressed? Two approaches will be presented in the following section with the aim of answering this question.

2. Crozier and Friedberg's approach of organized action

BFs have to juggle network contacts as if they are playing a game (Maurer 2001). This statement is very close to Crozier and Friedberg's[3] approach of organized action – a sociological one - that may suggest an

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[2] For example, Gabbay and Leenders (2002: 3) define social capital as "The set or resources, tangible or virtual, that accrue to a corporate player through the player's social relationships, facilitating the attainment of goals."

[3] Crozier was and Friedberg is a director of the "Centre de Sociologie des Organizations" in Paris. Their main academic works are "L'acteur et le systeme" (Crozier and Friedberg 1977) and "Local orders: dynamics of organized action" (Friedberg 1997). Criticizing the complete liberty of "acteurs" on the one hand, and the total constraint of actors by organizations on the other, they developed their approach of organized action.

approach that takes the dynamics, the multiple relationships and interests of actors in such scenarios into account.

For Crozier and Friedberg, an organized action is “the process through which the strategic interactions among a set of actors placed in a given field of action and mutually dependent for the solution of some common ‘problem’ are stabilized and structured” (1995: 75). Their approach is mainly based on four elements: a strategic *actor* (being an individual, group or any other collective entity) with his own interests interacting with other actors - also acting strategically; a concrete *system* formed by the interacting actors; the *game* as a mechanism of integration between actor and system where each actor has his own interests, but also the interest to keep a concrete system of action alive; *Power* as the capacity of action which is the unbalanced exchange of possibilities of action and which has four sources (i.e. mastery of specific expert knowledge, the control of information and communication resources, and organizational rules) (Crozier and Friedberg 1979, 1995).

Their approach is not one that distinguishes between market and hierarchy as abstract modes of coordination, but rather one explaining dynamic “empirical systems of actors” (see figure 2 in the appendix). According to Friedberg, this approach is also applicable to the study of innovation networks.

> *“This way of considering social action as a structuration and restructuration of the fields of action by the creation and stabilization of alliances and actor networks is applicable (…) to the study of the genesis and dissemination of scientific and technical discoveries and innovations. (…) the central question is to understand the social processes leading to the construction and organization of the competitive cooperation between a set of actors who are mutually dependent for the solution of a common problem, which they cannot solve by themselves and for the solution of which they have to secure the cooperation of partners who are also potential rivals” (Friedberg 1997: 122).*

With their approach they provide an explanation for the existence of [innovation] networks, which take an intermediary role between market and hierarchy. Moreover, it can explain the fact that different actors (e.g., scientists, venture capitalists, politicians etc.) with their own interests (e.g., gain reputation, profit etc.), and who are all interested in gaining as much as possible, nevertheless keep the game going (i.e. the dynamics of innovation networks). The element of power also fits into this explanation: scientists, for example, have scientific knowledge, whereas venture capitalists have know-how to access financial resources. The two can enter a reciprocal exchange relationship, but one from which one actor could gain more than the other one. Finally, the approach shows the double-edged character of innovation networks (i.e. collaboration and competition).

3. System dynamics modeling

The dynamic complexity of innovation networks can also be addressed by another approach. As it was stated in the first section, an innovation network is especially complex because of its *systemic* nature. It is the interrelatedness of parts that makes the production of an innovation a complex problem (Küppers & Pyka 2002). Consequently, adequate tools have to consider the actors’ heterogeneous composition, the possibility of feedback effects and a representation of dynamic processes through time. These requirements are congruent with the possibilities offered by simulation approaches (Küppers & Pyka 2002) and in an aggregated level by system dynamics[4].

Why simulation? The purpose of the analytical mathematical research branch in operations management is “to develop sophisticated relationships between narrowly defined concepts through developing new

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[4] A general discussion on simulation methods in social contexts can be found in Axelrod (1997) and in Gilbert & Troitzsch (1999). A comprehensive depiction of the System Dynamics approach is found in the book by John Sterman (2000), the current director of the M.I.T. System Dynamics Research Group.

mathematical relationships to study how the models behave under different conditions… to develop logically internally consistent theories" (Wacker 1998: 373-374). Such a mathematical model is more precise, although more restrictive. The translation of verbal theory to a mathematical representation results in the loss of richness (Repenning 2002). However, there are various benefits: computer simulation is seen as a technique that is able to represent, communicate and test theoretical concepts (Liebrand 1998) and, furthermore, enhances learning capabilities in complex settings (Sterman 2000)[5]. We therefore developed a model[6] (see figure 3) and a prototype simulator to analyze some of innovation networks' features with system dynamics modeling. The model is based on previous multi-agent, discrete models of innovation networks (Pyka, Gilbert & Ahrweiler 2002; Pyka & Saviotti 2002), and system dynamics models on trust and learning (Luna-Reyes 2003) and the model of path dependence found in the work of Sterman (2000).

The model particularly focuses on the first phases of innovation processes concerning the creation and generation of new products and ideas as well as the network associations at the early stages of development, as was partly explained in the first section of this paper. It addresses the effects of innovation networks for the generation of new scientific knowledge in competitive environments. In particular, it considers the impact of reinforcing loops, which can be found in knowledge generation processes (Luna-Reyes 2003) and in network structures in general (Sterman 2000). Feedback loops play a crucial role in competing firms and can bring path-dependent trajectories (Sterman 2000, Powell, Koput & Smith-Doerr 1996), a central issue in competitive settings that many biotechnology-based firms face (Liebeskind et al. 1996). It is a way to represent a *system* with its interrelated *actors* in the dynamic *game* of networking. And, particularly, it is a way to represent the proposal of Crozier and Friedberg. The mastery of expert knowledge (here scientific knowledge) becomes a source of power for one firm - in line with Crozier and Friedberg's ideas - and can decide which one is going to overcome its rival actor. At the same time the success of the actor (here a firm) permits more network utilization through improved profits which help to generate more knowledge and is a very important feedback loop (Schwaninger 2003; Sterman 2000). As the knowledge base grows, the competencies of the firm (i.e. actor) to generate patents grow too. Other aspect of the model is the issue of performance handled via patent generation (as suggested in Liebeskind et al. 1996). The number of patents (in a specific technological field) is taken as an indicator that reveals the volume and direction of the technological competencies in the system (Carlsson 2000). Another feature the attractiveness of the firm for potential scientific partners which is impacted by its success. This attractiveness will depend on its relative superiority in generating patents.[7]

In sum, the model regards scientific knowledge as the critical factor to address in innovation networks. The main features included are the learning effect of the network ("Network system effect") and the effect of previous knowledge in generating new knowledge, called "Internal actor learning". These reinforcing loops in the network may explain the path dependent trajectories for cycles of learning that are found in biotechnology environments (Powell, Koput & Smith-Doerr 1996). See figure 4 for a typical running of this model with this type of trajectories. Figure 5 shows the simulator control panel.

4. Conclusion

Summarizing, and using the frame and language of Crozier and Friedberg's ideas on *organized action*, it can be asserted that the characteristics and processes of innovation in the biotechnology sector show the importance of networking for firms (i.e. the *game* that integrates actors into the system). As such, our model especially addresses the early stages of technological and scientific development when the partner *actors* of the firm are usually research institutes and universities. These alliances form reinforcing loops in the structure of the *system*, which provide the firms with the needed resources (here knowledge) with which to

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[5] Furthermore, in the words of Robert Axelrod (1997): "Simulation is a third way of doing science. Like deduction, it starts with a set of explicit assumptions. But unlike deduction, it does not prove theorems. Instead, a simulation generates data that can be analyzed inductively. Unlike typical induction, however, the simulated data comes from a rigorously specified set of rules".

[6] The model's specification is found attached to this paper.

[7] The success of the firm also impacts other fields, for example, R & D investment (Sterman 2000; Pyka & Saviotti 2002; Schwaninger 2003).

overcome rival firms in these competitive environments. Fundamentally, these alliances can be seen as sources of *power* because of their tendency to enhance path-dependent trajectories via mastery of specific expert knowledge. These results are also consistent with the literature review on innovation networks in the biotechnology industry.

The Crozier and Friedberg's theory of organized action is a general way to explain a wide range of social action. To some degree Crozier and Friedberg's premises of organized action are represented in our model in order to investigate some of this approach's implications (for example, in this case the strength of reinforcing network processes that lead to specific trajectories in the *system*). System dynamics provides a laboratory for representing theories and for discovering the implications of assumptions that are not intuitively obvious (Repenning 2002). Thus, we have two different, but complementary, approaches focusing on the dynamics of innovation networks. Further exploration in this area may enrich the development of sociological theory and the study of these issues.

Appendix

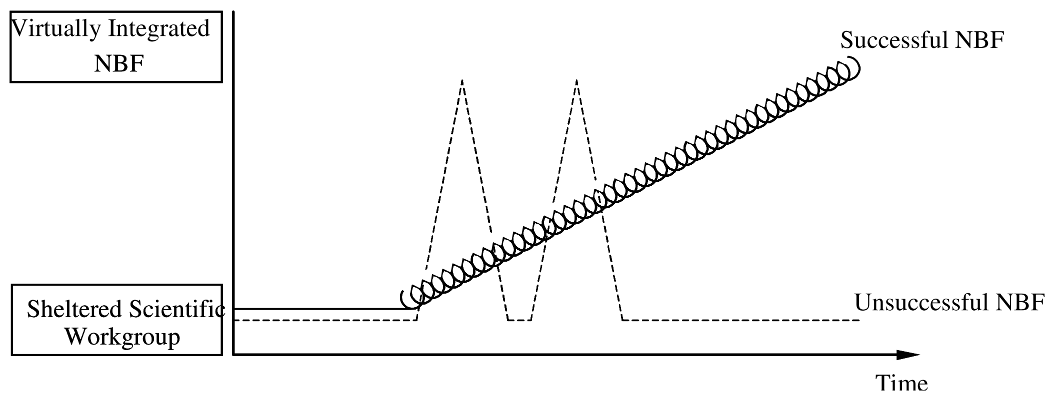

Figure 1: Development processes of successful and unsuccessful NBF (Maurer 2001: 39)

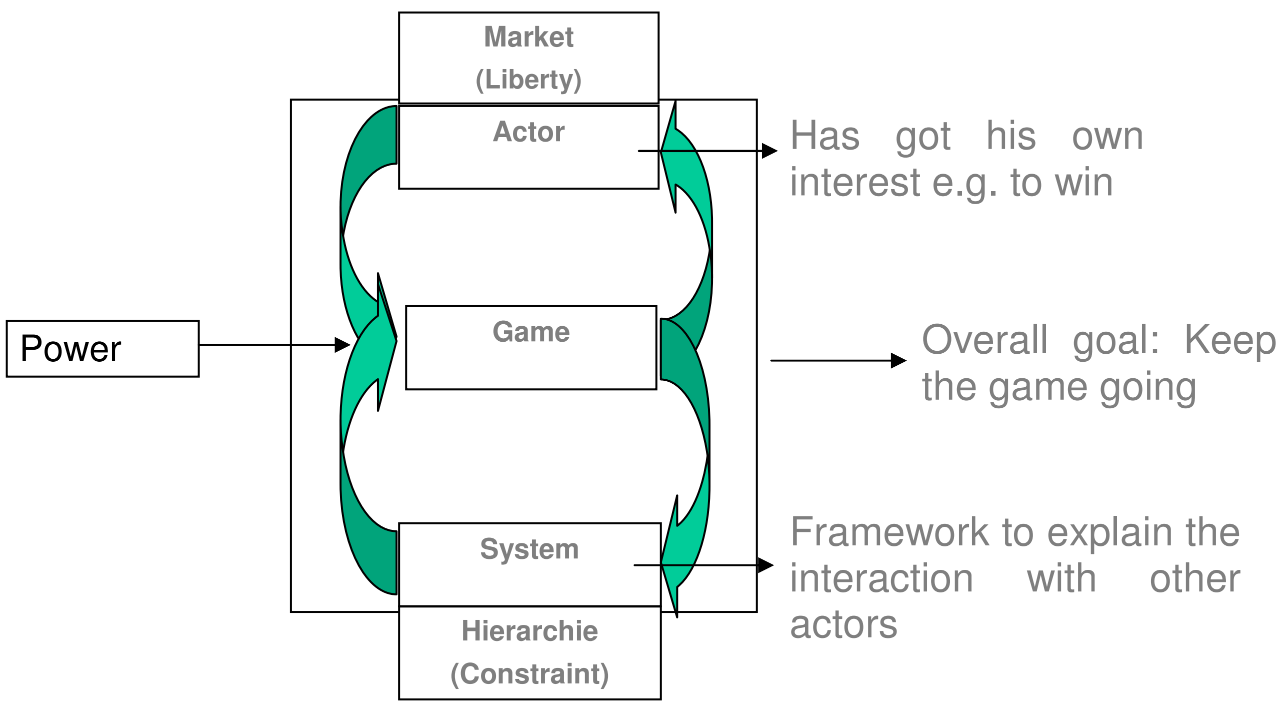

Figure 2: Visualization of Crozier and Friedberg's approach by Neuberger (2001) and own amendments[8].

[8] The game combines constraint (i.e. the constraint of the special field of action) and liberty (i.e. the creative rule interpretation of the strategic actors in a special field of action)

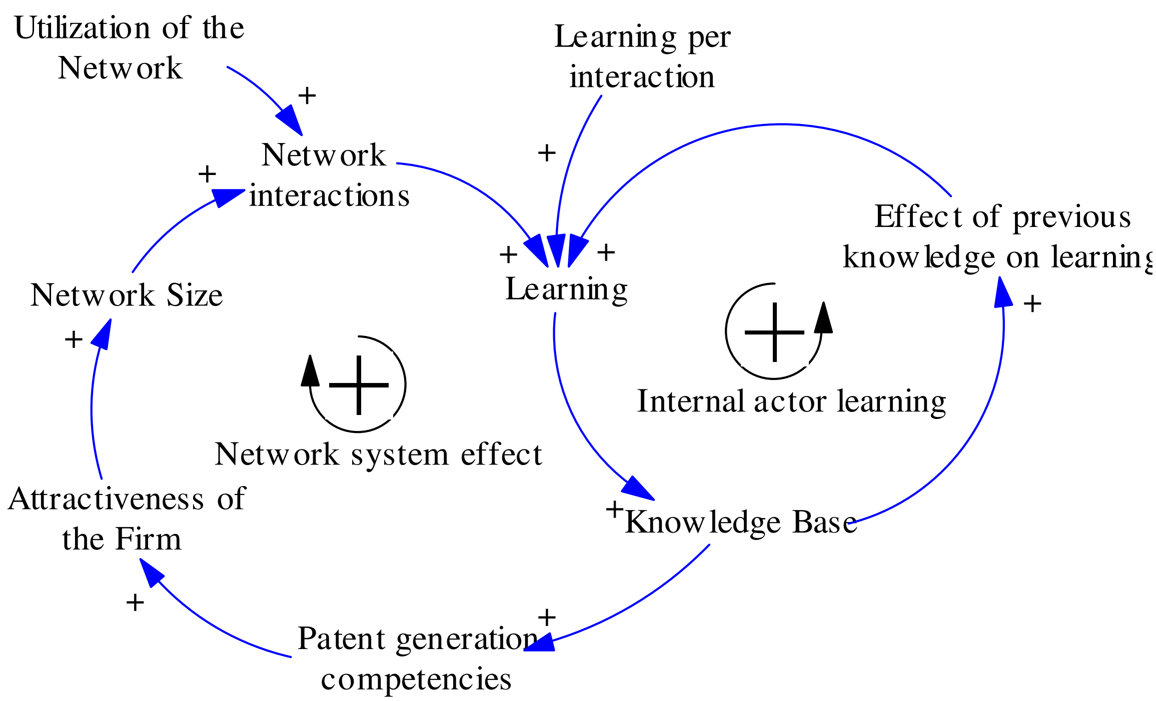

Figure 3: Main causal structure with the two positive reinforcing loops for one firm

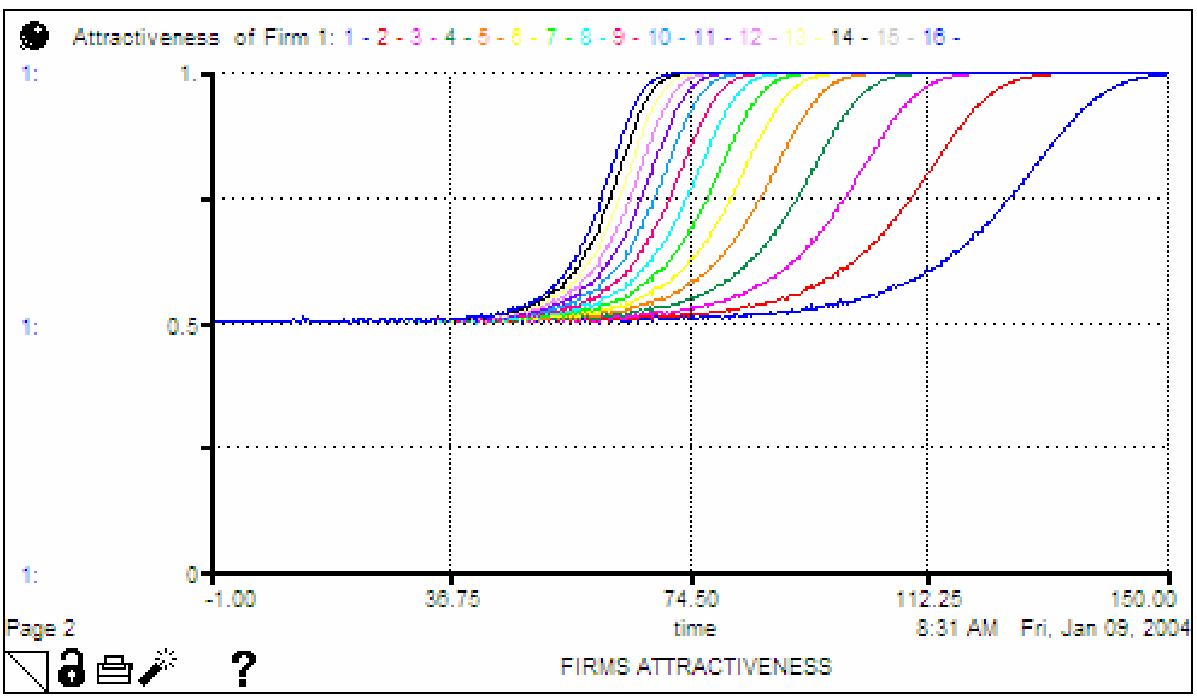

Figure 4: Different trajectories for attractiveness of firm 1 varying the sensitivity of competencies to knowledge base. Path dependence is the result with changes in the strength of the effect but not in the general patterns.

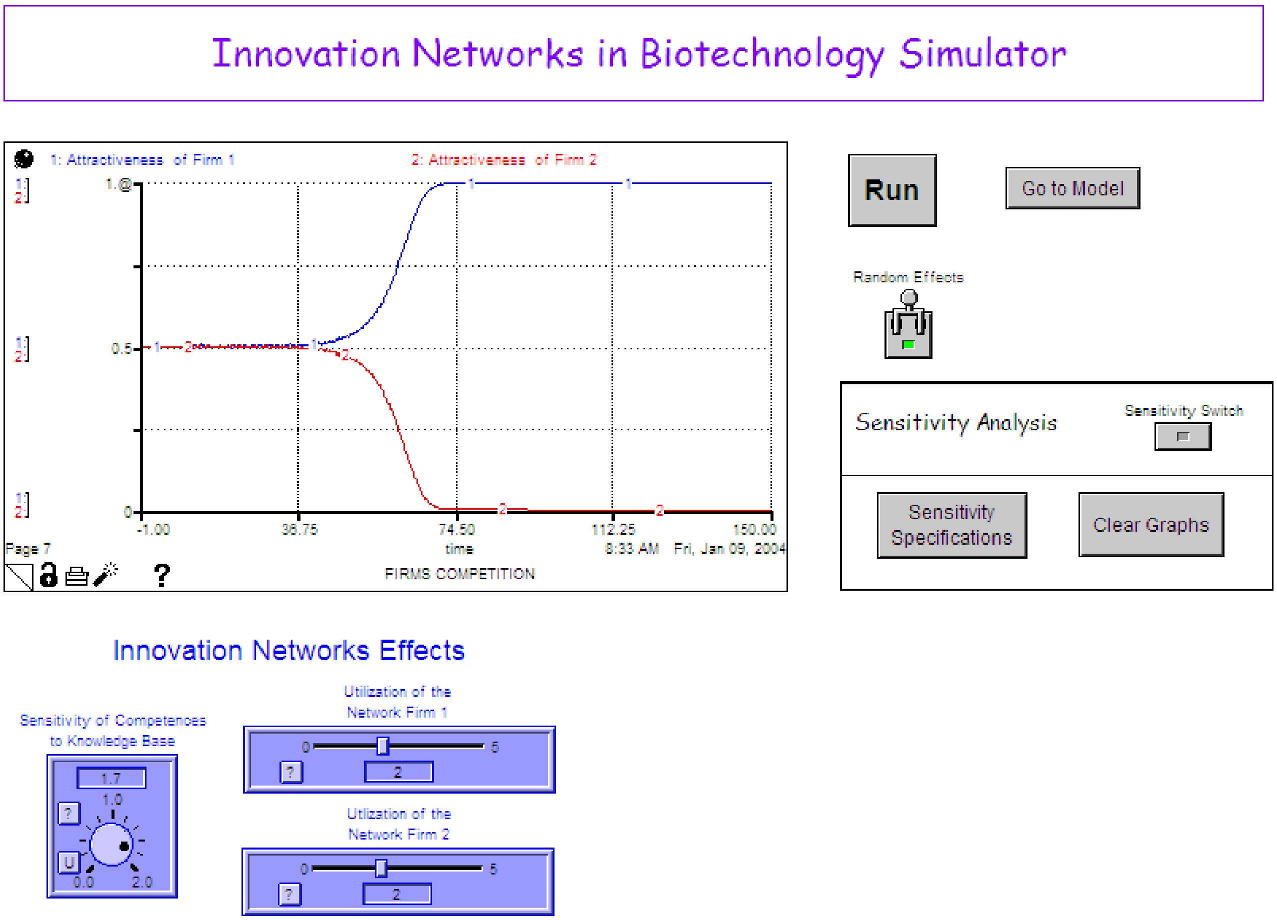

Figure 5: Simulator panel control. In the run pad there are the trajectories for two competing firms in the same environment. The levers change some critical variables in the *system*.

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FORMULATION AND SPECIFICATION OF THE MODEL

The model uses system dynamics in order to address some important features of innovation networks, particularly the first phases of innovation processes concerning the creation and generation of new products and ideas. System dynamics is accurate for analyzing the impact of feedback loops, delays and non-linearities in complex systems in depth, taking the whole system as the unit of analysis. The model addresses the effect of innovation networks on the generation of new knowledge in competitive environments. It particularly builds the impact of reinforcing loops, which can be found in knowledge and trust generation processes (Luna-Reyes 2003) and in path dependence structures in general (Sterman 2000). Feedback loops play a crucial role in competing firms and can lead to path-dependent trajectories (Sterman 2000, Powell, Koput & Smith-Doerr 1996), a central issue in competitive settings that many biotechnology based firms face (Liebeskind et al. 1996).

Knowledge and learning

A causal loop representation of the knowledge features of the model is found below. The model takes scientific knowledge as the critical factor to address via networking (Liebeskind et al. 1996). The main features included are:

- The learning effect in proportion to the size of the network ("Network system effect").
- The effect of previous knowledge on the generation of new knowledge (Luna-Reyes 2003), called "Internal actor learning".

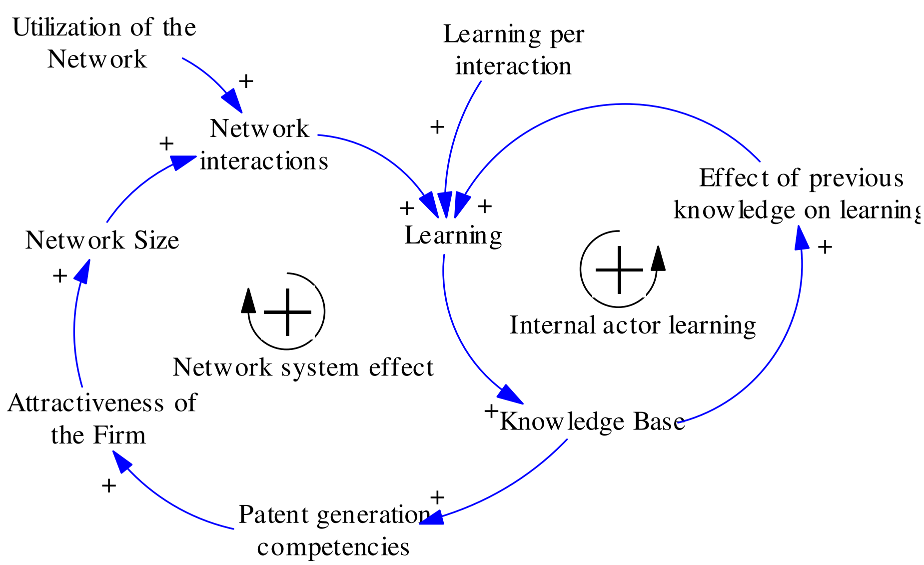


Figure A

Reinforcing feedback loops for one firm

A well-documented process in organizational learning is learning by doing, meaning that the learning process is a function of experience of previous work (Epple, Argote, & Devadas 1991; Luna-Reyes 2003). In the model it is assumed that the knowledge is a stock of the firm's accumulated learning over time[9]. It is also assumed that the firm increases its acquisition of knowledge due to the utilization of the network[10], measured by the number of contacts (and the size of the network) and also the effect of learning based on previous knowledge. This formulation, based on the work of Luna-Reyes (2003) and the formulation of stocks in system dynamics (Sterman 2000), becomes:

$$\text{Knowledge Base Firm}_i(t) = \int_{t_0}^{t} \text{Learning Firm}_i(s)ds + \text{Knowledge Base Firm}_i(t_0)$$

$$\text{Learning Firm}_i = \text{Network interactions Firm}_i * \text{Learning per interaction} * \text{Effect of previous knowledge on Learning Firm}_i$$

$$\text{Network interactions Firm}_i = \text{Network Size Firm}_i * \text{Utilization of the Network Firm}_i$$

$$\text{Utilization of the Network Firm} = \text{constant}$$

Feedback loops

Feedback loops as engines of patent generation competencies

As the knowledge base grows, the competencies of the firm to generate patents grow too. "Technological competencies are considered to be those components of the knowledge base required for building up production and innovation capabilities in a specific technology" (Pyka & Saviotti 2002). A plausible formulation is made, based on exponential effects. This formulation has similar application in the literature of system dynamics (Sterman 2000). The effect of the knowledge base on the innovation competencies could be modeled as:

$$\text{Effect of Knowledge base on Patents Generation Competencies Firm}_i = e^{\left[\text{Sensitivity of Competences to Knowledge Base} * \left(\frac{\text{Knowledge Base Firm}_i}{\text{Threshold for learning Effects}}\right)\right]}$$

Here, the competencies rise exponentially, as the Knowledge Base increases in relation to the threshold. The sensitivity captures the power of the effect. The threshold characterizes the magnitude of the knowledge base above which the network effect becomes influential[11].

[9] For simplicity the model does not include an "unlearning" or forgetting process in which the firm loses knowledge. This issue could be added in the same way:

$$\text{Knowledge Base Firm}_i(t) = \int_{t_0}^{t} \text{Learning Firm}_i(s)ds - \text{Unlearning Firm}_i(s)ds + \text{Knowledge Base Firm}_i(t_0)$$

An unlearning formulation can be found in (Luna-Reyes 2003).

[10] In Liebeskind et al.(1996), the indicator for scientific exchange is in terms of scholarly publications, although it is not a complete measurement. In their view it is a first approximation that can be also used as input to this model.

[11] Sterman (2000) uses this formulation to model the effect of the installed base of one product on its attractiveness, based on compatibility network issues.

The formulation of patent generation competencies is based on the suggestions of Sterman (2000) for multiplicative effects[12]:

$$\text{Patents Generation Competencies Firm}_i = \\ \text{Effect of Knowledgebase on Patents Generation Competencies Firm}_i * \\ \text{Effect of Other Factors on Patterns Generation Competencies Firm}_i$$

The effect of the knowledge base on the firm capacity to generate patents captures the learning effect: the larger the knowledge base, the greater the competencies to innovate[13] and the performance improves (Sterman 2000).

Performance measurement and success of the firm

Currently there is a wide-ranging discussion on the indicators of the generation of knowledge in technological systems. The abstraction of the model permits the taking of various performance measurements. For clarity's sake, it takes the number of patents (in a specific technological field) as an indicator that reveals the volume and direction of the technological competencies in the system (Carlsson 2000). Performance is therefore dealt with via patent generation (Liebeskind et al. 1996).

The firm's success impacts diverse fields, for example R&D investment (Sterman 2000; Pyka & Saviotti 2002; Schwaninger 2003). Another impact has to do with the firm's attractiveness to potential scientific partners in the innovation network. For potential network partners, the firm's attractiveness will depend on its relative superiority in generating patents relative to that of other competing firms. Hence, a formulation that meets this criterion – also common in the system dynamics field - is:

$$\text{Attractiveness of Firm}_i = \frac{\text{Patents Generation Competencies Firm}_i}{\text{Total Competencies of All firms}}$$

Increase of Network size

The model addresses the effect of the learning process in comparison to the size of the network, thus the relevant formulation deals with this issue according to the multiplicative formulation (Sterman 2000):

$$\text{Increase of Network Size Firm}_i = \text{Normal Increase of Network Size} * \\ \text{Effect of Attractiveness of Firm}_i \text{ on Increase of Network Size}$$

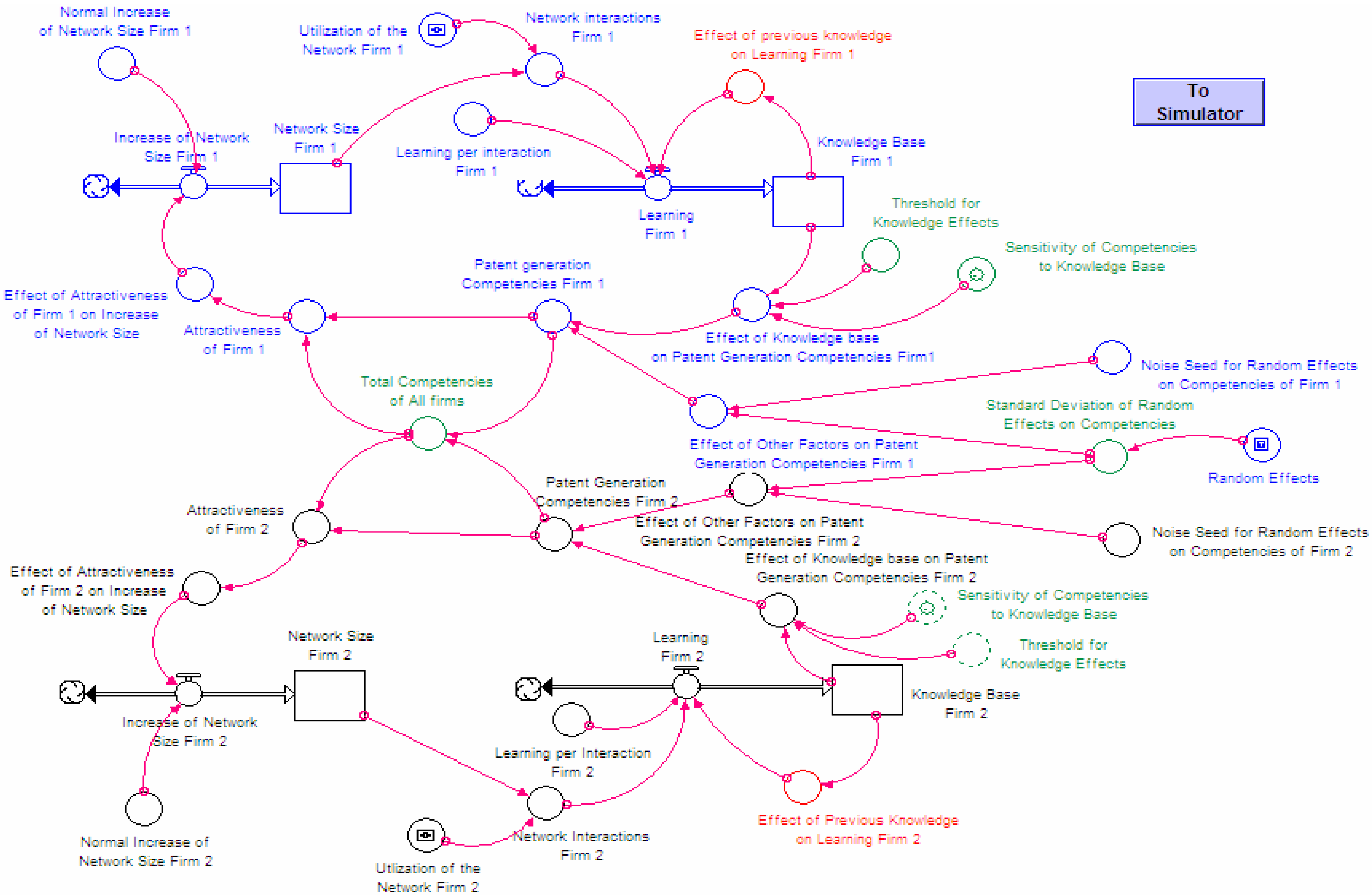
The Effect of Attractiveness on Network Size function represents the joining of a new partner as a result of the function of the firm's attractiveness.

[12] The formulation sets a variable Y to its reference value Y* multiplied by the product of n effects: Y = (Y*) x (Effect of X_1 on Y) x (Effect of X_2 on Y) x ... x (Effect of X_n en Y). These effects are usually non-linear functions (Sterman 2000). In this case, the variable 'Effect of Other Factors on Patterns Generation Competencies Firm_i" is the reference value – or normal value - in order to analyze the effect of knowledge base.

[13] Although using a different simulation approach, Pyka & Saviotti (2003) also formulate the competencies as a function of the firm's accumulated number of co-operations, the time spent in the activity and the firm's technological competencies. The effects are also captured via exponential functions.

MODEL

The next page shows the model developed for two competing firms. The following pages include the specification of each variable, description and units.



Normal Increase of Network Size Firm 1
Utilization of the Network Firm 1
Network interactions Firm 1
Effect of previous knowledge on Learning Firm 1
To Simulator
Increase of Network Size Firm 1
Network Size Firm 1
Learning per interaction Firm 1
Knowledge Base Firm 1
Learning Firm 1
Threshold for Knowledge Effects
Sensitivity of Competencies to Knowledge Base
Patent generation Competencies Firm 1
Effect of Attractiveness of Firm 1 on Increase of Network Size
Attractiveness of Firm 1
Effect of Knowledge base on Patent Generation Competencies Firm1
Noise Seed for Random Effects on Competencies of Firm 1
Total Competencies of All firms
Standard Deviation of Random Effects on Competencies
Effect of Other Factors on Patent Generation Competencies Firm 1
Random Effects
Patent Generation Competencies Firm 2
Attractiveness of Firm 2
Effect of Other Factors on Patent Generation Competencies Firm 2
Noise Seed for Random Effects on Competencies of Firm 2
Effect of Knowledge base on Patent Generation Competencies Firm 2
Effect of Attractiveness of Firm 2 on Increase of Network Size
Sensitivity of Competencies to Knowledge Base
Network Size Firm 2
Learning Firm 2
Threshold for Knowledge Effects
Knowledge Base Firm 2
Increase of Network Size Firm 2
Learning per Interaction Firm 2
Network Interactions Firm 2
Effect of Previous Knowledge on Learning Firm 2
Normal Increase of Network Size Firm 2
Utlization of the Network Firm 2

MODEL SPECIFICATIONS

Knowledge_Base__Firm_1(t) = Knowledge_Base__Firm_1(t - dt) + (Learning_Firm_1) * dt
INIT Knowledge_Base__Firm_1 = 1
DOCUMENT: The Knowledge base of Firm 1 in the relevant field
Knowledge Units

INFLOWS:
Learning_Firm_1 =
Learning_per_interaction__Firm_1*Network_interactions_Firm_1*Effect_of_previous_knowledge_on_Learning_Firm_1
DOCUMENT: Learning rate of Firm 1
Knowledge Units / month

Knowledge_Base__Firm_2(t) = Knowledge_Base__Firm_2(t - dt) + (Learning__Firm_2) * dt
INIT Knowledge_Base__Firm_2 = 1
DOCUMENT: The Knowledge base of Firm 1 in the relevant field
Knowledge Units

INFLOWS:
Learning__Firm_2 =
Effect_of_Previous_Knowledge_on_Learning_Firm_2*Learning_per_Interaction_Firm_2*Network_Interactions__Firm_2
DOCUMENT: Learning rate of Firm 2
Knowledge Units / month

Network_Size_Firm_2(t) = Network_Size_Firm_2(t - dt) + (Increase_of_Network_Size_Firm_2) * dt
INIT Network_Size_Firm_2 = 1
DOCUMENT: The size of the Network is measured via the number of partners (nodes) in the network of Firm 2

INFLOWS:
Increase_of_Network_Size_Firm_2 =
Effect_of_Attractiveness__of_Firm_2_on_Increase__of_Network_Size*Normal_Increase_of_Network_Size_Firm_2
DOCUMENT: The increase of the Network is influenced by the effect of the Attractiveness of Firm 2. Multiplicative formulation.
partner/month

Network_Size__Firm_1(t) = Network_Size__Firm_1(t - dt) + (Increase_of_Network__Size_Firm_1) * dt
INIT Network_Size__Firm_1 = 1
DOCUMENT: The size of the Network is measured via the number of partners (nodes) in the network of Firm 1
partners

INFLOWS:
Increase_of_Network__Size_Firm_1 =
Normal_Increase__of_Network_Size_Firm_1*Effect_of_Attractiveness__of_Firm_1_on_Increase__of_Network_Size
DOCUMENT: The increase of the Network is influenced by the effect of the Attractiveness of Firm 1. Multiplicative formulation.
partner/month

Atractiveness__of_Firm_1 = Patent_generation_Competencies_Firm_1/Total_Competencies__of_All_firms
DOCUMENT: The attractiveness of the firm depends on its relative superiority to generate patents relative to the other competing firms.
Dimensionless

Attractiveness__of_Firm_2 = Patent_Generation_Competencies_Firm_2/Total_Competencies__of_All_firms
DOCUMENT: The attractiveness of the firm depends on its relative superiority to generate patents relative to the other competing firms.
Dimensionless

Effect_of_Attractiveness__of_Firm_1_on_Increase__of_Network_Size = Atractiveness__of_Firm_1
DOCUMENT: The Effect of Attractiveness on Network Size function is discontinuous and represents the joining of a new partner in function of the attractiveness of the firm
Dimensionless

Effect_of_Attractiveness__of_Firm_2_on_Increase__of_Network_Size = Attractiveness__of_Firm_2
DOCUMENT: The Effect of Attractiveness on Network Size function is discontinuous and represents the joining of a new partner in function of the attractiveness of the firm
Dimensionless

Effect_of_Knowledge_base_on_Patent_Generation_Competencies_Firm_2 = EXP(Sensitivity_of_Competencies_to_Knowledge_Base * Knowledge_Base__Firm_2/Threshold_for__Knowledge_Effects)
DOCUMENT: The effect of the knowledge base on the Firm 2 capacity to generate patents.
Dimensionless

Effect_of_Knowledge_base__on_Patent_Generation_Competencies_Firm1 = EXP(Sensitivity_of_Competencies_to_Knowledge_Base * Knowledge_Base__Firm_1/Threshold_for__Knowledge_Effects)
DOCUMENT: The effect of the knowledge base on the Firm 1 capacity to generate patents.
Dimensionless

Effect_of_Other_Factors_on_Patent_Generation_Competencies_Firm_1 =
MIN(4,MAX(1,NORMAL(1,Standard_Deviation_of_Random_Effects_on_Competencies,Noise_Seed_for_Random_Effects_on_Competencies_of_Firm_1)))
DOCUMENT: It serves as reference value in order to analyze the effect of knowledge base for Firm 1. It includes effects of other possible factors exogenously
Dimensionless

Effect_of_Other_Factors_on_Patent_Generation_Competencies_Firm_2 =
MIN(4,MAX(1,NORMAL(1,Standard_Deviation_of_Random_Effects_on_Competencies,Noise_Seed_for_Random_Effects_on_Competencies_of_Firm_2
)))
DOCUMENT: It serves as reference value in order to analyze the effect of knowledge base for Firm 2. It includes effects of other possible factors exogenously
Dimensionless

Effect_of_previous_knowledge_on_Learning_Firm_1 = Knowledge_Base__Firm_1/Knowledge_Base__Firm_1
DOCUMENT: The effect of the knowledge accumulated increases new learning and therefore more knowledge.
Dimensionless

Effect_of_Previous_Knowledge_on_Learning_Firm_2 = Knowledge_Base__Firm_2/Knowledge_Base__Firm_2
DOCUMENT: The effect of the knowledge accumulated increases new learning and therefore more knowledge.
Dimensionless

Learning_per_Interaction_Firm_2 = 0.2
DOCUMENT: Learning gain per contact Firm 2
Knowledge Units / contact

Learning_per_interaction__Firm_1 = 0.2
DOCUMENT: Learning gain per contact Firm 1
Knowledge Units / contact

Network_interactions_Firm_1 = Network_Size__Firm_1*Utilization_of_the_Network_Firm_1
DOCUMENT: It multiplies the utilization of the net by Firm 1 (measured by the frequency of contacts with partners, monthly) with Network Size (number of partners).
contact / month

Network_Interactions__Firm_2 = Network_Size_Firm_2*Utlization_of_the__Network_Firm_2
DOCUMENT: It multiplies the utilization of the net by Firm 2 (measured by the frequency of contacts with partners, monthly) with Network Size (number of partners).
contact / month

Noise_Seed_for_Random_Effects_on_Competencies_of_Firm_1 = 900
DOCUMENT: Input to the random function for Firm 1 to variate the effect of other factors
Dimensionless

Noise_Seed_for_Random_Effects_on_Competencies_of_Firm_2 = 1000
DOCUMENT: Input to the random function for Firm 2 to variate the effect of other factors
Dimensionless

Normal_Increase_of_Network_Size_Firm_2 = 1
DOCUMENT: The standard increase of the Firm 2 Network Size. Default = 1 (This means, one new partner by month at least is incorporated to the firms network)
partner/month

Normal_Increase__of_Network_Size_Firm_1 = 1
DOCUMENT: The standard increase of the Firm 1 Network Size. Default = 1 (This means, one new partner by month at least is incorporated to the firms network)
partner/month

Patent_generation_Competencies_Firm_1 =
Effect_of_Knowledge_base__on_Patent_Generation_Competencies_Firm1*Effect_of_Other_Factors_on_Patent_Generation_Competencies_Firm_1

DOCUMENT: Multiplicative formulation depending of the effect of the knowledge base of Firm 1 and other exogenous factors.
Dimensionless

Patent_Generation_Competencies_Firm_2 = Effect_of_Knowledge_base_on_Patent_Generation_Competencies_Firm_2 * Effect_of_Other_Factors_on_Patent_Generation_Competencies_Firm_2
DOCUMENT: Multiplicative formulation depending of the effect of the knowledge base of Firm 2 and other exogenous factors.
Dimensionless

Random_Effects = 1
DOCUMENT: Binary variable to turning "on" or "off" the random effects

Sensitivity_of_Competencies_to_Knowledge_Base = 1
DOCUMENT: Sensitivity captures the power of the effect.
Dimensionless

Standard_Deviation_of_Random_Effects_on_Competencies = STEP(0.01,10)*Random_Effects
DOCUMENT: Standard deviation for random effects
Dimensionless

Threshold_for__Knowledge_Effects = 10
DOCUMENT: The Threshold characterizes the magnitude of the knowledge base above which the effect becomes influential
Knowledge Units

Total_Competencies__of_All_firms = Patent_generation_Competencies_Firm_1 +Patent_Generation_Competencies_Firm_2
DOCUMENT: The sum of all the competencies of all the firms
Dimensionless

Utilization_of_the_Network_Firm_1 = 2
DOCUMENT: Number of scientific contacts per partner per month made by Firm1. It measures the strength of the utilization of the network made by Firm 1
(contact/partner) / month = contact / (partner*month)

Utlization_of_the__Network_Firm_2 = 2
DOCUMENT: Number of scientific contacts per partner per month made by Firm2. It measures the strength of the utilization of the network made by Firm 2
(contact/partner) / month = contact / (partner*month)