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The coevolution of endogenous knowledge networks and knowledge creation

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Abstract

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STATE-OF-THE-ART

Simulation models are useful to explain evolutionary processes. They have been widely used to model knowledge networking, the process by which agents interact to create knowledge. They have also been used to model knowledge creation by agents in a network.

So far, simulation models have somehow neglected the interrelation of the processes of knowledge creation and network formation. This interrelation arises because agents choose the partners with whom they are going to create knowledge and, as they do, change their future behavior and outputs.

Most of the empirical studies aiming at explaining the relation between the network of an agent and his performance use measures of the network around one agent as a determinant of the output of the agent, and thus disregard any possible feedback. As a consequence, results are mixed and inconclusive. Some studies indicate that knowledge is a collaborative process, that is to say, that the more intensely agents collaborate, the more knowledge they create. Other studies suggest that the number of collaborators is not a determinant of the performance of agents and finally, some studies find that collaborating can be somehow harmful for performance.

These different studies consider an exogenous network structure, i.e. they take this structure as given and predict its impact on knowledge creation. This is not realistic, mainly because agents choose their collaborators for specific reasons, including reputation or previous performance. Thus, network formation and creation are endogenous processes. The structure of the network affects the output of agents, which determines the future structure of the network. Previous empirical studies did not account for this feedback, which can explain the ambiguous results they obtained.

RESEARCH GAP

Nonetheless, few studies have theoretically modeled the interaction of the network and the creation of knowledge, and none has analyzed their coevolution. The aim of this study is to cover this gap by crafting a simulation model of an endogenous and evolving network of agents that create knowledge. Simulations of the model will generate different theoretical scenarios of the parallel or opposite coevolution of knowledge networks and knowledge creation, reconciling the confronting empirical evidence.

THEORETICAL ARGUMENTS.

In each step, the agents will form a network and create a certain amount of knowledge. The probability that two agents collaborate at some time increases with previous collaboration and with the attractiveness of the agents. The amount of knowledge created by an agent depends on the structure of his ego network and on the stock of knowledge he possesses. Both functions are based on empirical and theoretical literature.

METHOD

The model has been programmed using R. For the simulations, $n=100$ agents interact for $T=500$ periods, with the first 100 periods as warm-up. Different behaviors emerge for different sets of parameters, depending mainly on whether collaborations are profitable (if the amount of knowledge created from collaborations is high enough compared to the cost of maintaining a collaboration), the amount of knowledge created from the previous knowledge, and whether collaborators are chosen depending on their previous history of collaboration or on their attractiveness. The effect of these parameters is isolated in some of the simulations.

RESULTS

The simulations of the model show that all the different cases of knowledge creation through collaboration can be originated by a single process. Moreover, the model draws attention to several features of the process that could otherwise be neglected. First of all, the positive relation between the number of collaborators and the performance of agents can be due to the process of partner selection rather than to the process of knowledge creation. Also, the model signals that in the creation of knowledge in networks, the main determinant of performance is not necessarily the collaboration itself. Furthermore, it indicates the importance of considering a possible negative effect of collaborations for knowledge creation. These results have important implications for the design of policies aiming at improving the process of knowledge creation in networks.

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Abstract

Theoretical literature acknowledges the interplay between knowledge creation and network collaboration, but related formal models are scarce. Empirical studies show conflicting evidence about the relation between knowledge creation and network collaboration (positive, none, or negative), perhaps because they take little account of their endogeneity. The simulation model in this paper deepens formal theoretical understanding and reconciles the evidence by analysing feedbacks between both processes.

The model also highlights some aspects of these feedbacks that may not be desirable. Collaboration can increase disparities between agents because of the cumulative nature of knowledge creation. Collaboration may not boost knowledge creation, if collaborators are an innocuous byproduct of the attractiveness of most productive agents. Most productive agents may attract many collaborators and become less productive if the cost of networking is high, and even unproductive if the cost of networking is higher than its contribution to knowledge creation. The model offers some keys to design policies that avoid these scenarios.

1 Introduction

Simulation models are useful to explain evolutionary processes. They have been widely used to model knowledge networking, the process by which agents interact to create knowledge. Some interesting examples are the models of inventor networks by Ter Wal (2013), researchers collaboration by Petersen et al. (2012), or interfirm R&D alliances by Ahrweiler et al. (2004). They have also been used to model knowledge creation by agents in a network. For those models, knowledge can be considered as an abstract idea (Cowan and Jonard, 2003), or can be measured as an output of the abstract knowledge, as the number of scientific papers for researchers (Borner et al., 2004), or new products for firms (Malerba et al., 1999).

So far, these simulation models have somehow neglected the interrelation of the processes of knowledge creation and network formation. This interrelation arises because agents choose the partners with whom they are going to create knowledge and, as they do, change their future behavior and outputs (Baum et al., 2010). Nonetheless, few studies have theoretically modeled the interaction of the network and the creation of knowledge, with some important exceptions such as the work by Cowan and Jonard (2004), who emphasized the complex nature of knowledge creation through collaboration but did not analyze their coevolution. In this work, we claim that this scarcity of theory accounting for the feedback between both processes can explain the apparently conflicting empirical evidence on the relation between the network and the performance of agents.

Such empirical evidence belongs to a wide and growing body of literature that seeks to explain the relation between the network of an agent and his performance (for a broad review, see Ozman, 2009 and Phelps et al., 2012). Most of those empirical studies use measures of the network around one agent (his ego network) as an explanation of the output of the agent, and thus disregard any possible feedback. As a consequence, results are mixed and inconclusive. It is unclear, for instance, how the simplest measure of the ego networks, the number of collaborators (or degree) of an agent, affects his performance. Some studies indicate that knowledge is a collaborative process, that is to say, that the more intensely agents collaborate, the more knowledge they create. An example of this behavior can be found in the work by Ahuja (2000), where collaborations can provide agents with resources and new information. Other studies suggest that the number of collaborators is not determinant of the performance of agents. For example, Bell (2005) found no significant relation between the number of formal ties of a firm and its innovativeness. He suggested that “institutional ties were used solely for the transmission of relatively well-known information”. Finally, some studies find that collaborating can be somehow harmful for performance. As McFadyen and Cannella Jr. (2004) put it, “the greater the number of different relationships that an individual must maintain, the less the effort the individual can put into creation activities”. Thus, at some point, agents can have too many collaborators and start to underperform compared to those with less partners.

These different studies consider an exogenous network structure, i.e. they take this structure as given and predict its impact on knowledge creation. This is not realistic, mainly because agents choose their collaborators for specific reasons, including reputation or previous performance (Wagner and Leydesdorff, 2005; Balland et al., 2012). Thus, network formation and creation are endogenous processes. The structure of the network affects the output of agents, which determines the future structure of the network. Previous empirical studies did not account for this feedback, which can explain the ambiguous results they obtained.

The aim of this study is to cover this gap by crafting a simulation model of an endogenous and evolving network of agents that create knowledge. Simulations of the model will generate different theoretical scenarios of the parallel or

opposite coevolution of knowledge networks and knowledge creation, reconciling the confronting results of the existing literature.

The structure of the paper is as follows. Section 2 presents the coevolution model of knowledge creation and knowledge networks. Section 3 shows the results that can be extracted from the simulations. Finally, Section 4 discusses the different results.

2 The model

Let us consider a model where a set of $S = \{1, \dots, n\}$ agents interact over T periods of time. In each step, they will form a network and create a certain amount of knowledge. The network will be represented by its adjacency matrix t , where $t(i, j)$ takes the value 1 if i and j collaborate in step t , and 0 otherwise. The degree (or number of collaborators) of agent i in step t will be $d_t(i) = \sum_j t(i, j)$. This is the simplest indicator to measure the ego network, and it is typically used in the empirical literature as in Bell (2005) or Cooke and Wills (1999). The network in each step will be created depending both on the network and the knowledge created in previous steps. As the network is created in each step, links are allowed to break and form over time. Likewise, the amount of knowledge created in each step will depend first on the amount of knowledge created in previous steps, and also on the structure of the network. Agents start the simulations as homogeneous. As the simulation develops, agents become heterogeneous in their knowledge endowment and in their ego network. A link between two agents can be created in any step even if they did not collaborate in the past. Likewise, two agents can stop an existing collaboration if the link is not updated in a following step.

Knowledge networks are evolving: links between agents break and form as a result of strategic decisions (Barabasi et al., 2002; Fleming and Frenken, 2007). These strategic decisions have usually two components, the previous history and the attractiveness of agents (Ahrweiler et al., 2004). Having previously collaborated increases willingness to engage in knowledge creation (Cowan et al., 2006; Baum et al., 2010), so the probability that a link forms between two agents increases with previous collaboration. Also, more experienced and successful agents are more likely to find partners (Wagner and Leydesdorff, 2005; Balland et al., 2012), so the probability of collaborating will increase with the attractiveness of the agents. As a result, the structure of the network affects not only agents' performance, but also their future behavior (Ahuja, 2000; Cowan et al., 2006).

The probability that agent i collaborates with agent j is a linear combination of their previous history and the attractiveness of agent j (Equation 1); respectively weighted by λ and $1 - \lambda$ constrained to $[0, 1]$. The attractiveness of an agent depends on the amount of knowledge he has previously created, relative to the knowledge created by the rest of the agents in the network. This function is inspired by the preferential attachment algorithm (Barabasi and Albert, 1999;

Albert and Barabasi, 2002).

$$P(i \rightarrow j, t) = \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} s(i, j) + (1 - \frac{1}{\tau}) \sum_{s=t-\tau}^{t-1} \frac{\kappa(j, s)}{\max_k \kappa(k, s)} \quad (1)$$

The probability that agents i and j collaborate is that either of them collaborates with the other (Equation 2). In taking probabilities we account for the fact that they can be willing to collaborate but may not be able to do so for some reason. The probability that a link breaks, that is, that a collaboration in time $t - 1$ does not continue in time t , is $1 - P(i \rightarrow j, t)$.

$$P(i \leftrightarrow j) = P(i \rightarrow j \cup j \rightarrow i) \quad (2)$$

Equation 3 shows the functional form for the creation of knowledge. The performance of agents in a knowledge network can be deeply influenced by the structure of the network (De Solla Price, 1965; Guler and Nerkar, 2012). The amount of knowledge created by agent i at time t , $\kappa(i, t)$, depends on the structure of his ego network and on the stock of knowledge he possesses. On the one hand, the more collaborators he has the more knowledge he produces, which is captured by parameter θ . Thus, θ can be interpreted as the amount of knowledge created in each collaboration. On the other hand, collaborations can be costly (McFadyen and Cannella Jr., 2004; Ozman, 2009), and thus a very high number of collaborations can hamper the creation of knowledge. This is captured by parameter γ and the square of the number of collaborations, so small numbers of collaborations will have a positive effect, but high numbers will decrease the knowledge created. No negative amounts of knowledge or negative costs are allowed, so $\theta \geq 0$ and $\gamma \geq 0$.

$$\kappa(i, t) = \theta \frac{1}{\tau + 1} \sum_{s=t-\tau}^t d_s(i) - \gamma d_t(i)^2 + \alpha \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \kappa(i, s) \quad (3)$$

Finally, knowledge is a cumulative process: new knowledge can be created from previous knowledge (Jaffe et al., 2000). Parameter α measures how much new knowledge is created from the stock of knowledge of agent i , and hence it accounts for the cumulateness of knowledge. The length of the time window is τ , the number of periods before the knowledge becomes obsolete.

This functional form implicitly assumes that there are only two possible sources of new knowledge for an agent: collaborations and the pool of knowledge he already possesses. Due to the recombinant nature of knowledge (Konig et al., 2011; 2012), if an agent was not to collaborate at any time for some reason, the possible amount of new combinations of his existing knowledge would be limited. At some point, he would not be able to keep on creating new knowledge unless he started collaborating. Thus, given this functional form for the creation of knowledge, α is necessarily bounded to $[0, 1]$.

This function is similar to the one used by Konig et al. (2011, 2012), although it differs in the amount of knowledge created by each collaboration. In

their model, the amount of knowledge created by an agent is a recombination of the knowledge stocks of the agent and his neighbors. In line with this approach, we add a new dimension to the effect the knowledge of neighbors has in the knowledge of an agent. In our model, the amount of knowledge of the potential neighbors is a determinant of the network creation function. Thus, the knowledge stocks of the neighbors influence the amount of knowledge agents create through its influence in whether or not they become collaborators. Although it does not appear explicitly in the function of knowledge creation, it implicitly affects its result.

Notice that the agents' actions are not the result of an explicit decision making process, as they do not develop strategies that maximize some objective function like in the game theoretical literature (see for example Azagra-Caro et al., 2008 or Westbrock, 2010). This approach is closer to the evolutionary literature (Nelson and Winter, 1982) as it does not require any assumption on the rationality of the agents.

Param.	Interpretation	Constraints
θ	Amount of knowledge created from each collaboration	$\theta \geq 0$
γ	Cost of collaborating	$\gamma \geq 0$
α	Amount of knowledge created from the stock	$0 \leq \alpha < 1$
λ	Weight of previous collaboration in the probability to collaborate	$0 \leq \lambda \leq 1$
τ	Length of the time window (number of periods before the knowledge becomes obsolete)	$\tau \in \mathbb{N}$

Table 1: Parameter table

3 Results

The behavior of the simulations depends on the values of the parameters. In this section we will present different scenarios for different sets of parameters. For the simulations, we will consider a set of $n = 100$ agents interacting for $T = 500$ periods, with a warm-up of 100 periods.

The results of the simulations are not dependent on the length of the time window τ as long as it is higher than 1. For $\tau = 1$ only two possible scenarios appear: either a complete network or an empty network emerge very quickly, so agents collaborate either with everybody else, or with no one else¹. In the simulations we will use a value of $\tau = 5$, which is found standard in the literature (Song et al., 2003; McFadyen and Cannella Jr., 2004; Agrawal, 2006; Fleming et al., 2007).

The behavior of the model is depicted in the following figures. For each figure, the number of collaborators and the amount of knowledge of each agent

¹For $\tau = 1$, the agents producing the maximum amount of knowledge maintain their collaborators with probability 1. Either the network remains empty and no one produces knowledge, or one of the agents starts producing knowledge, attracts the rest, and the network becomes complete and stable.

is plotted for the last 400 steps of the simulations, resulting in 40000 different points. Figures 1, 2 and 3 show an example of the three possible scenarios described in the empirical literature.

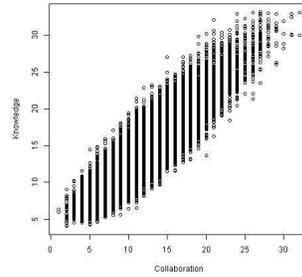


Figure 1: Positive coevolution

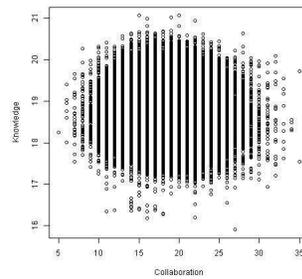


Figure 2: Independent coevolution

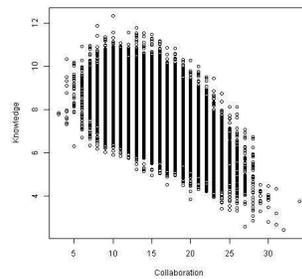


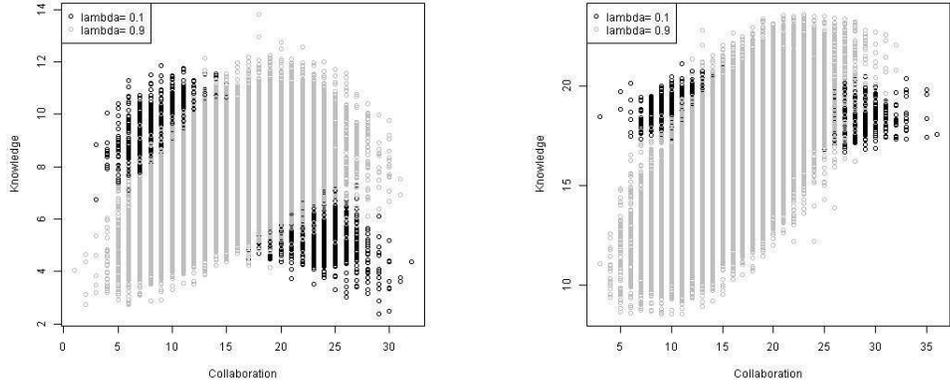
Figure 3: Negative coevolution

When the amount of knowledge created through collaborations, θ , is high

enough compared to the cost of maintaining a collaboration, γ , collaborations are profitable. In such a case, the process can produce two distinct patterns: a positive coevolution (Figure 1) or an independent coevolution (Figure 2). First, if the amount of knowledge created from the stock, α , is low, knowledge comes mainly from collaborations. Thus, the relation between the number of collaborations and the creation of knowledge is usually positive (Figure 1). On the other hand, when α is high, both collaborations and previous knowledge are important sources of new knowledge. The effect of both parameters is mixed: the performance of agents with many collaborators and agents with a small number of collaborators but a large stock of knowledge is similar. Thus, the coevolution is independent, as the number of collaborators seems not to affect the creation of knowledge (Figure 2).

Finally, collaborations are not necessarily profitable. If the cost of maintaining a collaboration, γ , surpasses the amount of knowledge created through collaborations, θ , every new collaboration is prejudicial for the performance of agents. In such a case, the amount of knowledge created is decreasing in the number of collaborations, and the observed coevolution is opposite (Figure 3). Without considering a drawback to collaboration, this coevolution pattern can never appear. Thus, it is important to consider some kind of collaboration costs in order to replicate the negative coevolution of collaboration and creation of knowledge.

To fully grasp the complexity of the model described here, let us consider a change in only one of the parameters, leaving the rest unchanged. A change in a parameter of the knowledge equation will clearly result in changes in the knowledge created by the network, and a change in the parameters of the network formation equation should result in changes in the network structure. However, the results of changing one parameter are much more interesting, because of the relation between those two functions. Figures 4 and 5 show some examples of the complex behavior of the model due to the feedback between the process of knowledge creation and the process of network formation.



(a) From a negative to a positive coevolution (b) Differences in the amount of knowledge created

Figure 4: Effect of an increase in λ

Consider that we fix all the parameters in the knowledge creation function and vary only λ , the weight of having previously collaborated in the probability to collaborate, from 0.1 to 0.9 (Figure 4). When $\lambda = 0.1$, the probability to collaborate depends mainly on the attractiveness of agents; while when $\lambda = 0.9$, it depends mainly on whether or not the two agents have collaborated in the previous steps. With this increase in λ , the process can switch from a negative to a positive coevolution scenario (Figure 4a). In such a case, the positive coevolution is not driven by the knowledge creation function but by the network formation process. That is to say, the coevolution is positive not because agents with more collaborators create more knowledge, but because the most productive agents attract more collaborators. For such a high value of λ as 0.9, all agents have a negligible attractiveness except the most productive ones. Thus, only the most productive agents can attract any new collaborator, while the rest just renew their old collaborations.

If the underlying behavior for a low value of λ was an independent coevolution (Figure 4b), then collaborations are not harmful for the knowledge creation process. In such a case, increasing the value of λ can lead to a certain Matthew effect: the most productive agents attract more collaborations and thus perform even better, increasing the performance difference with the least productive agents. Thus, some agents perform better, and many agents perform worse, if collaborations are based on previous history rather than on attractiveness.

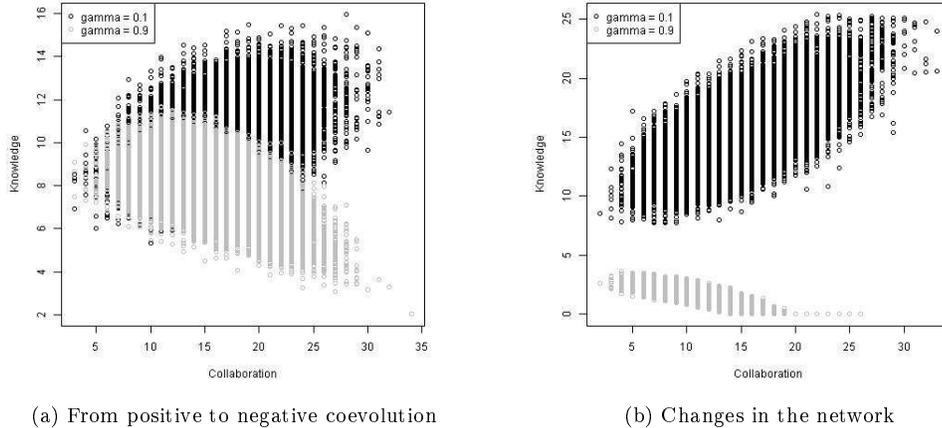


Figure 5: Effect of an increase in γ

A similar behavior can appear for changes in parameters of the knowledge function. Increasing γ , the cost of collaborating, from 0.1 to 0.9 can change the overall coevolution from positive, where collaborations are profitable, to negative, where collaborations are harmful for the knowledge creation process (Figure 5a). Of course, the amount of knowledge created will be higher for lower values of this cost. Moreover, the change can be so drastic that only agents with very few collaborators are able to produce any knowledge at all (Figure 5b). In such a case, increasing γ will lead to a lower number of collaborations in the resulting knowledge network. This looks similar than the mechanism shown by Figure 3. However, there is a difference. Figure 3 represents that the cost of network collaboration is higher than the amount of knowledge it creates. In Figure 5, this is not necessary: most productive agents in early periods attract collaborators and, if the cost of collaboration is high enough (even if lower than the amount of knowledge it creates), they may become less productive in later periods (even less productive than agents with fewer collaborators).

4 Discussion and conclusions

This paper presents a simulation model of the coevolution of knowledge networks and knowledge creation. This kind of model is specially important in current times, when knowledge appears to be increasingly an interactive process and a deeper understanding can help improving the performance of the system in a more efficient way. This paper suggests that different scenarios of coevolution can arise depending on the importance of collaborations for knowledge creation, the importance of previous knowledge and the process of partner selection. The

simulations show that the model is suited to reproduce a stylized process of knowledge creation through collaborations. Two simple rules of behavior are enough to reproduce the different scenarios found in the empirical literature, that correspond to different cases of apparently conflicting empirical evidence. Thus, all those different cases of knowledge creation through collaboration can be originated by a single process.

Moreover, it draws attention to several features of the process that could otherwise be neglected. First of all, the positive relation between the number of collaborators and the performance of agents can be due to the process of partner selection rather than to the process of knowledge creation. This has important implications for researchers, as it points out the importance of taking into account the endogeneity of the network when analyzing the effect of collaborations in knowledge creation.

Furthermore, the model indicates the possible negative effect of collaborations for knowledge creation. Despite the general belief that collaborations boost performance and knowledge creation, it is important to remember that collaborations are not costless. The cost of establishing and maintaining a collaboration can sometimes surpass the benefits of collaborating. Managers should consider these costs when deciding whether or not to collaborate with other agents.

Finally, it points out the importance of the process of partner selection. The study indicates that the process of knowledge creation is hampered by “myopic” partner selection processes, based on previous history rather than attractiveness. If agents are bounded to their previous collaborations, the overall performance of the system is lower whereas if they can freely establish new links or break them, the levels of performance achieved by the system are higher. Policy makers aiming at improving knowledge creation process should try to reduce the importance of having previously collaborated in agents’ decision to collaborate, as well as reducing the costs of collaborating. In such a case, policies aiming at improving the creation of knowledge can focus at improving the legal and social framework. If previous history is important due to a context of high uncertainty and instability, a solution can be improving the legal framework in order to reduce the risk of hold-up and thus increase agents’ willingness to interact to unknown partners. In the case of a social context where agents have few opportunities to meet new partners and thus start new collaborations, encouraging agents to increase the number of collaborations can be enough to force the creation of linkages with new partners. When the goal of a policy is to increase both knowledge creation and collaboration, they can be achieved by focusing on improving collaboration.

The usefulness of having a model that reproduces a stylized process of knowledge creation through collaborations is manifold. The prediction of the coevolution of knowledge creation in a network can help agents to settle the convenience to enter an already existing knowledge network. It can also predict the possibility of a certain Matthew effect, so it can be considered for policy design. Additionally, such a model can be used for the diagnosis of an operating system. It can help figuring out what happened in a process that was well fitted and suddenly changed its behavior.

This paper has some limitations. First of all, the simulation model suggests different lines of action for different underlying processes. Picking out the right process is essential to choose the right action to implement. In order to address this issue, the model will be empirically validated in future research. This empirical validation will help to identify the most likely parameters of a real knowledge creation process. It can also lead to a comparison of different knowledge creation processes. Furthermore, in a next stage of research it would be desirable to implement policy actions. The model will have to be able to incorporate parameter changes through time. Then, the policy actions suggested for the different scenarios will be tested through simulations, in a secure and costless way.

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