Learning by Modeling: Insights from an Agent-based Model of University-Industry Relationships

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Abstract

Learning is central in so-called knowledge societies. In order to cope with the complexity of socio-economic phenomena new forms of learning are necessary. We argue that learning-by-modeling is contributing to our knowledge of complex phenomena. The idea of learning-by-modeling is introduced by applying an Agent-based model of University-Industry Relationships.

1 Introduction

In what is increasingly thought as a "knowledge society" continuous learning is supposed to be a fundamental requirement upon which knowledge and economic growth are built. Obviously in a complex world learning is not an easy task. To the contrary learning is itself a complex phenomenon. In terms of a taxonomy different forms of learning have been identified as so-called *learning-by-concepts* [Malerba, 1992] of which so-called *learning-by-doing* is most prominent. A particular form of learning-by-doing, which concerns research activities, can be labeled *learning-by-modeling*: A problem of interest is described in an abstract form in an equation system and the static as well as dynamic features of the model are analyzed. The gained insights are applied to generate a better understanding of the underlying problem.

Choosing an adequate mathematical representation as well as an adequate degree of complexity reduction to trace the model analytically is everything but an easy task. For instance researchers in economics face a severe trade-off between the complexity of the problem under investigation, which is characterized by multi-agent dynamics and often self-reinforcing processes and the scope of an analytical framework which at best can give a detailed partial picture of a multifaceted reality. In such a contexts, Agent-Based Models (ABMs), are increasingly considered as a promising alternative: on the one hand, it builds upon theories and empirical evidence, on the other hand it integrates them, suggesting different and more comprehensive ways to look at complex phenomena, thus providing the potential to explain results which otherwise might look contradictory. Modelling experience can be viewed as a learning process itself: it is an adaptive struggle in a world full of complexity. In this struggle we often become aware of how little we know about the actual problem under investigation.

The aim of this paper is to discuss how ABM methodology can contribute, through a *learning-by-modelling* process to increase our understanding of complex phenomena. We will make use of a model of University-Industry Relationships (UIRs) in the bio-pharmaceutical sectors, which analyzes interactions and the underlining knowledge dynamics between heterogeneous agents involved in research. A detailed description of this model and of the simulation results can be found in [Triulzi *et al.*, 2009]. For the purpose of this paper we will use this modelling experience to sustain our argumentation. Note that many other ABMs can serve the same purpose.

The paper is organised as follows: We start with a conceptualization of modelling as double-loop learning processes (section 2); a brief description of UIRs as an example of a complex phenomenon characterized by unclear empirical evidence will be presented (section 3.1). From this we claim the necessity of a more *complex-friendly* way of analysis: ABM (section 3.2). In 3.3 we describe the Agent-Based-UIRs model and section 3.3 introduces to the main findings. Finally a collection of insights from the modelling experience is summarized (Section 4). We conclude that the Agent-Based-UIRs model can be viewed as an example of a double-loop learning process.

2 Modeling as a double-loop learning process

ABMs can be thought as a laboratory for theory improvement. Deichsel and Pyka [2009] and Brenner

and Werker [2007] argue, that abductive methodologies, which consist in starting with studying the facts, devising simple assumptions and then going back and forth between assumptions and their implications, are perfectly suited for a refinement of theory. ABMs contribute to improve the understanding of complex phenomenon because the modeling experience is itself a learning process. More precisely, modeling is intrinsically a double-loop learning process. Indeed, as argued by Argyris and Schön [1996], two types of learning can be distinguished: single and double loop learning. The difference concerns the refinement of the theories and the assumptions upon which learning is grounded. The former is based on a mechanism of control and correction. When the outcome of an action differs from its expected result, a process of search and correction of the causes of the mismatch begins. This process is based on feedbacks that are analyzed using the basic knowledge of the actor which, in single loop learning, is an instrument of the analysis but is not itself the object of learning. Contrariwise, double-loop learning does not consider basic knowledge as a dictum. Hence it includes all kinds of involved knowledge. Double loop learning is suited for the investigation of complex phenomena because basic knowledge improvements are foreseen. Without doubt, this is the case for modelling experiences. Theoretical elements must be included in ABMs as well as a general awareness of the stylised facts related to the research object. In the modelling process all these elements are subject to validations which ultimately contribute to advance our knowledge on the issue.

3 An example: an ABM of University-Industry Relationships

We choose as an example for modeling experience our model of UIRs in the bio-pharmaceuticals sectors. A brief description of the model (section 3.3) and its context (sections 3.1 and 3.2) help to make the reader familiar with it and to better understand the peculiarities of the double-loop *learning-by-modeling* process.

3.1 A complex phenomenon: University-Industry Relationships

The way innovation is pursued in life sciences industries is strongly influenced by the advent of the biotechnology paradigm and the spreading of university patenting. In this industry UIRs have emerged as a major platform for knowledge exchange and innovation. Despite their dramatic expansion and the growing awareness in the economic and medical literature, there is only inconsistent and incomplete evidence with respect to the long-run effects on the innovativeness of the research system.

On the one hand, many authors [e.g. Angell, 2004] suggest that UIRs can potentially damage the long run innovativeness of the research system in life sciences. Following this literature, UIRs have modified the reward system for academic researchers, introducing a personal and institutional incentive to do more applied research. The possibilities to increase industry funding stemming from the commercialization of academic research potentially push universities away from the pure basic in favour of a more applied research, in order to increase the probability to end up with patentable research outcomes. The consequences might be harmful for the system because it generates a situation in which less scientists and less academic institutions are engaged in basic research, which is a fundamental component of the whole system and necessary to generate continuously innovations.

On the other hand, many studies [e.g. D'Este et al., 2005], show that access to additional financial resources and to industry skills are reasons for university researchers to interact with industry. Some authors [e.g. Breschi et al., 2007] postulate the existence of a resource effect: interactions with industry, providing larger cognitive and financial resources, increase the productivity of academic scholars and university institutions in terms of publishing and patenting, thus increasing their visibility and reputation. A self-reinforcing virtuous circle is generated which boosts research productivity.

This contradictory evidence even worsens because only a few empirical studies also consider the system which surrounds these interactions. The role of other actors, like government, is largely neglected. So is the bi-directionality of the knowledge and technology transfer between universities and industry. Even if there are several studies focusing on the nature of public research funding, this issue has been considered in isolation. Studies have produced inconsistent evidence: some highlight complementarities between public and private R&D while others claim a substitutive relationship (for a comprehensive literature survey, see David et al., 2000).
UIRs are clearly a complex phenomenon. Therefore, these relationships call for a more comprehensive analysis which attempts to integrate the various dimensions and extend our current knowledge.

3.2 In praise of ABMs

The lack of a generally accepted evaluation of UIRs can be traced back to two shortcomings: (i) the complexity of these relationships makes it difficult to analyse their multiple correlated effects. However, the efforts to consider the role of all the actors which are engaged in the bio-pharmaceuticals' innovation systems and to analyse how these relationships affect each other (i.e. universities, industry and governments) is worth to be made. To focus only on a selected group is misleading. (ii) Traditional scientific tools have only limited possibilities to disentangle the underlying complexity. Qualitative (interviews etc.) as well as quantitative analysis (econometric models etc.) are extensively applied to study UIRs. They are extremely useful to understand specific aspects of UIRs and to gain insights into the complex relations. But they all miss a key issue, namely the interaction sphere dealing

with knowledge flows between different actors. Hence, we are in one of the frequent cases in which the complex nature of the phenomenon under investigation leads to unclear empirical evidence. How to shed light on this ambiguity?

We claim that UIRs are driven by the need to access and exchange specialized and generic knowledge. In a science-based and knowledge-intensive sector, like bio-pharmaceuticals, actors are heterogeneously specialized in a relatively narrow knowledge space. This is true for firms as well as for universities (though slightly less strict). The cumulative nature of knowledge in these fields leads to the creation of self-reinforcing mechanism between the accumulation of knowledge and expertises and the generation of successful innovations. These mechanisms are treated as a 'nuisance' causing simultaneity or heteroscedasticity problems. Obviously, when it comes to the empirical analysis of evolutionary processes based on knowledge dynamics, a major problem as expressed by Keith Smith emerges: "Neither learning nor the capabilities which result, seem to be measurable in any direct way" [2005, p.151]. As shown by several models belonging to the SKIN family [among others Gilbert et al., 2001] knowledge dynamics can be effectively analysed through multi-agent simulations based on interactions between heterogeneous and bounded rational agents. These models show that knowledge dynamics have to be placed central because they are the origin of agents' success/failure on a micro-level and key to understand causes and consequences of aggregate phenomenon at the macro-level. We argue that ABMs main strength is to allow a more comprehensive view on knowledge dynamics which allows for important additional insights. Of course 'traditional' analytical tools are not discarded. On the contrary, they provide stylized facts, and contribute to theory formation. ABMs build on them and allow going one step further: they integrate traditional analyses and provide the prerequisites for substantial theory improvement.

3.3 The model

Our model reproduces R&D and knowledge dynamics in the bio-pharmaceutical sector, with a particular focus on the role of UIRs. We refer to a model of innovation networks originally developed by Gilbert, Pyka and Ahrweiler [e.g. 2001]. This model is further refined in subsequent works in which it has been applied to study a variety of issues related to knowledge dynamics, learning and collaboration between agents. We extend the original model to reproduce the research environment of bio-pharmaceutical industries, explicitly taking into account different classes of agents moved by diverse aims and rewards (universities, biotech and pharmaceutical firms), multiple channels of interactions (research collaborations, licensing and sponsored research) and different research outputs (three classes of patents and drugs). The goal of the model is to analyze knowledge dynamics between the

actors, and to test the effects of agents' interactions on their knowledge base and, ultimately, on the innovativeness of the research system with the help of simulation experiments.

3.3.1 Types of agents

The model's population is composed of universities (UNIs), large diversified firms (LDFs) and dedicated biotech firms (DBFs). There are two further actors, a National Research Agency (NRA) and venture capitalists (VCs). These latter agents are funding actors (of universities and biotech firms respectively) which are not actively engaged in research.

Agents differ according to their knowledge base. The model's representation of the knowledge base of agents draw on the concept of 'kene' developed by Gilbert [1997] and applied in previous simulations of knowledge dynamics in innovation networks. The knowledge base of each agent, its *kene*, consists of a vector containing different 'units of knowledge' called quadruples. Each quadruple includes: a research direction (RD) which allows to differentiate between universities (mainly engaged in basic research) and firms (mainly engaged in applied research), a capability (C) which stands for the particular technological discipline in which actors are engaged (pharmaceutical or biotechnology), an ability (A) which reveals the actor's specialization in his/her capability field and an expertise (E) which shows for how long an agent has been active in a certain ability.

3.3.2 Decision mechanisms

Agents have to take two important decisions: (i) they have to allocate their funds between the different research-related activities: own research projects and joint research projects (for all the agents), licensing, sponsoring and clinical trials (only for LDFs). This choice follows a satisfycing behaviour. (ii) If they decide to allocate part of their resources to joint research projects, they have to choose one or more partners according to two partnerships strategies: a conservative strategy which aims to find as similar agents as possible, and a progressive strategy, which aims to find as different partners as possible.

3.3.3 Environment and interactions

The model's environment plays an important role: agents are aware of competition as well as the possibility to cooperate. Firms screen their environment when they decide on their allocation strategy. Periodically firms compare their allocation strategy with the average allocation per activity of the most successful firms, i.e those in the first quartile of firms ranking, belonging to the same sector. If a firm is successful it does not change its allocation strategy. Firms that are not successful change their strategy by imitating successful firms.

As in Gilbert et al. [2001] the process of own and collaborative research is based on the combination of selected elements of an agent's knowledge base which forms a so-called innovation hypothesis (IH). In the

case of joint research the project knowledge base is a combination of parts of the knowledge bases of the involved agents. Some quadruples of the agents' kenes are randomly recombined to form a project innovation hypothesis. If the project is successful, the actors with an absorptive capacity above a critical threshold acquire the knowledge of the joint innovation hypothesis which has been contributed by the project partner(s), though with a reduced experience level.

3.3.4 Model's dynamics

Each simulation run consists of several iterations, i.e. cycles of research. A cycle starts, when actors choose to start a joint, an own research project or both. In the former case, actors look for partners and subsequently jointly run the project (and share the project costs). In the latter case, the actors set up and run the project in isolation. The project lasts several periods and finally is evaluated. If the project is successful a patent is granted. There are three kinds of possible outcomes in the model (ranked from the least to the most innovative): (1) C-class patent, (2) B-class patent and (3) A-class patent. Which outcome is generated depends on the research direction of the actors (a basic research direction increase the likelihood to get an A-class patent) and on the variance of the involved capabilities (the higher the variance, the higher the outcome's value). The probability of success which is positively related to the agent's experience level, is higher for an applied research direction and negatively depends on the variance of the capabilities involved.

If the patent is granted to an university or a DBF, the patent holder enters the market for research and try to find a LDF willing to acquire a license. If the patent is originally granted to a LDF, the firm can directly conduct clinical trials and try to develop a new drug to earn revenues. Eventually the actors re-invest the money that they have gained at the end of the research cycle in new research projects and a new cycle begins.

3.3.5 Results

Several Monte Carlo simulation experiments based on a standard and some alternative scenarios are performed. Results of different scenarios are compared tested for statistical significance. Results are shown in Figure1. The upper left graph shows the dynamics of the average research orientation of universities for two simulations: a standard scenario in which universities are allowed to interact with industry (both DBFs and LDFs), and a second one in which universities were the only agents in the population. One immediately sees that in the latter case universities maintain a strong focus on basic research (lower values of the average research direction). This shows that relationships with industry do increase incentives for universities to engage in applied research.

The upper right graph shows the results for the test of the so-called 'resource effect hypothesis'. On the vertical axis we find the percentage of innovative patents (A-class) generated by universities relative to total university patenting. Again two experiments are performed. In the case of interactions between universities and DBFs (standard scenario) university patenting is more innovative (larger percentage of A-class patents) than in the case in which these interactions were not permitted (no_DBFs scenario). This finding shows that universities do not enjoy cognitive resource effects related to interaction with industry. We also tested the hypothesis of a financial resource effect generated by licensing revenues from LDFs. The results in terms of the relative number of A-class patents have not proved to be statistically significant. However we found that interactions with LDFs increase the total number of university patents but without influencing their innovation value.

We also tested the effects of interactions with universities on DBFs innovative capabilities. The percentage of innovative patents (A-class) out of the total number of DBFs patents is on the vertical axis of the lower left graph in Figure 1. The two lines represent the values of this percentage in two different simulations: the standard scenario and a scenario in which universities were excluded from the population (DBFs could not interact with them). The difference in the trends shows that DBFs greatly benefit from knowledge exchange with universities. This shows that despite the missing cognitive resource effects on the universities side, this effect is visible for the industry partners. In other words, biotech firms benefit more than universities from the knowledge exchange between each other.

Finally our simulation experiments show that governments can effectively reduce the harmful effects of UIRs on the universities research direction. Higher incentives for basic research can be restored through a larger basic research public funding budget. This is shown in the lower right graphs in Figure 1. On the vertical axis we find the average research direction of universities. The different lines represent different scenarios in which the basic research public budget is progressively increased (MAX_NRA_rd3/4/5). The graph shows that a larger government basic research funding prevents the shift of university research orientation from basic to applied research.

4   Insights from the modeling experience

The application of the Agent-based simulation methodology generates new insights on the complex phenomenon of University-Industry Relationships.

Our experiments reject the hypothesis of a positive influence of a cognitive resource effect on university innovative patents productivity and partially reduced the influence of the financial resource effect.

Nevertheless, knowledge exchange processes are still a crucial characteristic of UIRs. Intensive interactions between universities and DBFs do not produce an increase in universities' innovative capabilities. Instead, they reduce the total number of patents coming from academic research. This, however, does not mean that there are no benefits from these interactions. Through joint research projects, an exchange of knowledge between universities and
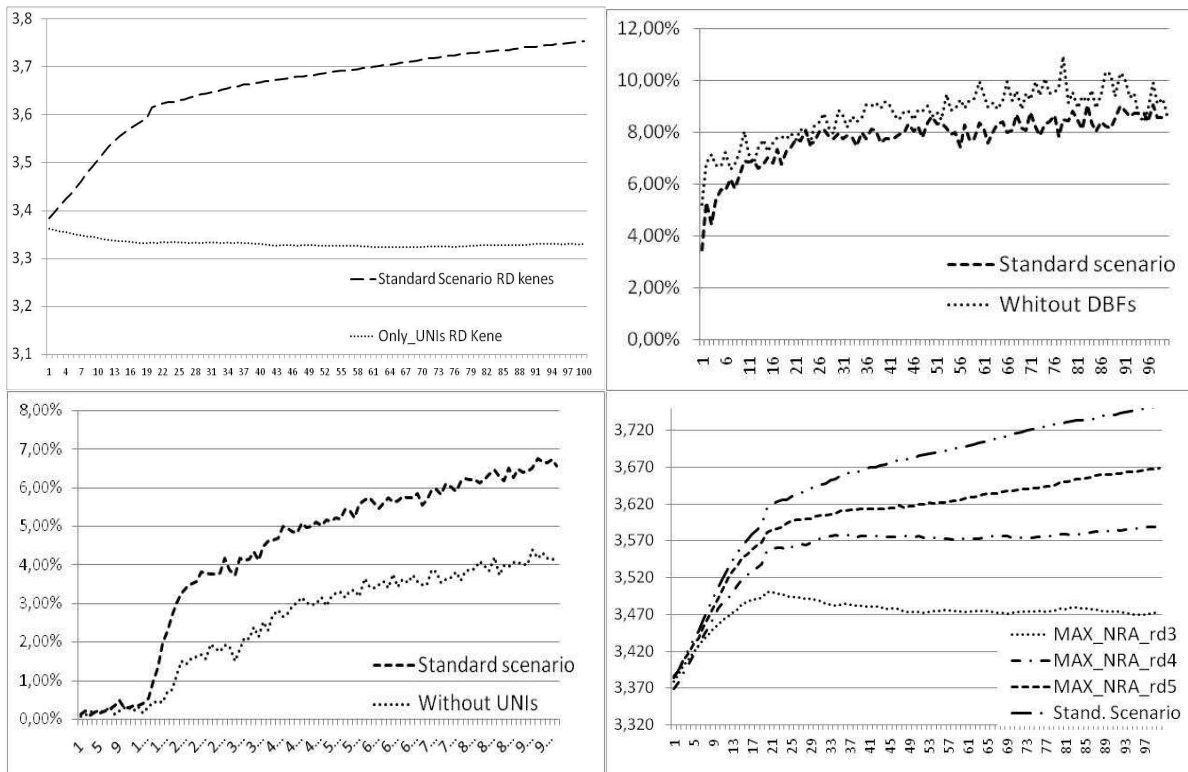
Figure 1

biotech firms occurs. This newly acquired capabilities and abilities expand the university knowledge base, thereby increasing its heterogeneity, but this is not sufficient for a larger patent productivity of universities. Many universities might not have the right skills to deal with applied research, namely, they might not be experienced to deal with a knowledge that is far from their traditional research orientation.

Our findings also show that when a complex phenomenon like UIRs involving heterogeneous actors is analyzed, one has to consider all of its multi-facetted aspects. In particular, our results show that UIRs cause a significant increase in the innovative potential of biotech firms. This is due to a threefold effect: (i) interactions with universities expand DBFs' knowledge bases, allowing biotech firms to absorb new kene elements focusing on fundamental research. (ii) UIRs increase the variance in their capabilities and, (iii) they have a positive effect on DBFs' networking experience. Therefore our results highlight the importance of UIRs concerning technology and knowledge flows. These finding suggest that, besides universities, new scientific knowledge is increasingly generated by biotech firms.

Finally our results show that even if public and industry research funding are considered to substitute each other, in bio-pharmaceuticals they are complementary. According to our results government basic research grants are important to counterbalance the different aims and incentives provided by industry

which further enlarge the market failure, especially in the long run. Accordingly, government research policies should be oriented to raise the public research funding budget with the aim to ensure that an adequate amount of fundamental research is undertaken.

5   Conclusions

Innovation takes place in extremely complex systems which are characterized by heterogeneous actors, multi-dimensional interactions and multiple knowledge flows. The increasing complexity creates new challenges for scholars and can be disentangled only by the integration of several methodologies.

We argue that ABM can play a key role in this respect. In particular double-loop *learning-by-modeling* challenges what we think to know about the object of the analysis. An example of this double-loop learning process, focused on UIRs has been provided. As argued by Argyris and Schön [1996], double loop learning starts from theory and refines it through a verification and validation cycle in which the theory itself is checked and improved. In a similar vein, Deichsel and Pyka [2009] recommended that modelers should start with reasonably simple assumption based on theoretical elements and stylized facts and hence entering the process of going back and forth between assumptions and implications. In the case of the model presented above we use as initial inputs of the modeling process a combination of theories and insights gained from empirical evidences as well as stylized facts about UIRs. This theories greatly help to set

up a more realistic view of agents (bounded) rationality, and of their satisficing behavior. Our modeling effort benefits from the large literature on the nature of innovation processes involving science and technology interactions. We also started from theories of innovation networks which are now largely accepted as a crucial source of innovation driven by interactions between specialized agents and the underling knowledge exchange. Finally we build on theories on the relation between cognitive distance and innovation outputs [Nooteboom, 1992 and 1999] or the relations between research orientation and innovation output to set up some starting formulas.

Obviously we match theories with some facts and figures about UIRs in the bio-pharmaceutical industry. For instance, we calibrate the functional relations as well as the parameters of our model by running several test-simulations and compare results with empirical data about the percentages of A/B/C drugs in US. Then we pick up those parameters and refine the formulas in a way that the results are reasonably similar to real world data. Finally the robustness of our parameters is tested by a sensitivity analysis. This way one can still have some surprising findings compared to the initial expectation of the modeler. This eventually leads to interpretation of the results that really provides new insights and viewpoints. In our model this has been the case for the un-experience of many universities to deal with a too radical different research orientation compared to their ancestral one. Of course, results depend on assumptions. Practically what we say is that *if we assume* bounded rational agents and the relations between research orientation and innovative outputs and between cognitive distance and innovative outputs, then university-industry relationships lead to the knowledge dynamics that we have highlighted. However, it is crucial to notice that these assumptions have not "fallen from the sky" but are results of a sort of inductive process driven by the interaction among theoretical elements, stylized facts and learning by modeling.

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