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MODELLING INNOVATION NETWORKS OF GENERAL PURPOSE TECHNOLOGIES – THE CASE OF NANOTECHNOLOGY

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ABSTRACT

With the emergence of nanotechnology a new General Purpose Technology is shaping the evolution of many economies. Knowledge intensive industries such as nanotechnology evolve in innovation networks consisting of various actors. With their wide ranging applicability innovation networks of General Purpose Technologies differ greatly from other innovation networks. Based on the multiagent simulation model "Simulating Innovation Networks in Knowledge Intensive Industries" we propose a framework to model and simulate the emergence of General Purpose innovation networks.

1 INTRODUCTION

Nanotechnology, the manipulation and control of matter at the scale 1-100 nanometres, proves to have an increasing socio-economic impact on its way to become 'the key-technology of the 21st century' (Bhattacharya and Shilpa, 2011, p. 349). It has already found applications in various industrial sectors such as information and communication technology, pharmaceuticals, materials and manufacturing, or biotechnology. This broad applicability is why nanotechnology is a so-called "General Purpose Technology (GPT)" (Bresnahan and Trajtenberg 1995). With its broad range of applicability and spread in many industries, its innovation networks strongly differ from those of other emerging technologies. In this paper, we want to address these differences of GPT innovation networks and suggest ways how to model them. The proposed simulation model is based on the SKIN model, which simulates the dynamics of knowledge in innovation networks. The adaptations of the model will allow us to simulate the distinct characteristics of GPT innovation networks within a setting of other technology innovation networks most of which are potential application sectors for the GPT. By applying Genetic Algorithms (GA) we are also able to track the dissemination of the GPT knowledge, and to implement an evolutionary idea of knowledge creation and development as well as various forms of learning and collaboration.

2 THEORETICAL BACKGROUND: THE GENERAL PURPOSE CHARACTER OF NANOTECHNOLOGY

The term General Purpose Technology was coined by Bresnahan and Trajtenberg (1995) who define GPTs as 'characterized by pervasiveness, inherent potential for technical improvements and 'innovational complementaries'.' (Bresnahan and Trajtenberg 1995, p. 83). This means that the GPT should spread to many sectors (pervasiveness), it should get better over time (improvement) and thereby making it cheaper to use and it should trigger innovations in other sectors (Bresnahan and Trajtenberg 1995, Jovanovic and Rousseau 2005). In literature, the term 'enabling technologies' is often used to describe the latter effect:

combined with others technologies in the application sectors (AS), the emergence of GPTs can lead to new innovations as it triggers the development of complementary technologies (Bresnahan 2010).

Undisputed examples for GPTs can be found in Computers (Bresnahan and Trajtenberg 1995) and the steam engine (Lipsey, Carlaw, and Bekar 2005) besides others. However, there is discussion about which technology can be considered as being a GPT, for instance some authors include the laser or biotechnology (Lipsey, Bekar, and Carlaw 1998). With nanotechnology one of the most recent examples of a GPT is said to be unfolding currently. Nanotechnology is widely regarded as a GPT, as it shows pervasiveness, inherent potential for technical improvements and innovational complementaries (cf. Youtie, Iacopetta, and Graham 2007). As the particularities of GPTs not only show in their innovation networks but also in several stylised facts, these facts on the evolution of nanotechnology will also be incorporated in the model.

3 GENERAL PURPOSE TECHNOLOGIES IN INNOVATION NETWORKS

The evolution of innovation networks of knowledge intensive sectors has been studied extensively over the last years, focusing for example on biotechnology (Pyka and Saviotti 2002) or nanotechnology (Ludeña et al. 2008), often restricted to a certain region or country. Innovation networks consist of various heterogeneous actors, such as universities, research institutions, small and large companies, governmental institutions, intermediaries and funding institutions. Collaboration allows the agents to share resources and exchange knowledge. By recombining their knowledge innovations emerge from which the network members can profit. Within the literature studying innovation networks, how these links become established and how the actors collaborate is of special interest. From answering these questions one can understand how the knowledge disseminates within the network, how the knowledge is recombined combined, how do actors learn from each other, i.e. how does new knowledge emerge and lead to new innovations.

There are some issues where the evolution of 'standard' knowledge intensive sectors differ from the evolution of GPTs. First, GPTs are technologies, which are on the one hand evolving themselves by innovation, but on the other hand are triggering innovation in multiple other sectors. Developments in the GPT are not restricted to the GPT sector, but can effect various other sectors in which the GPT is already applied, or can be applied in future because of the new developments taking place. However, this also includes feedback effects. With the number of application raising, returns on innovation in the GPT also increases, making R&D even more lucrative (Bresnahan and Trajtenberg 1995). Second, as the GPT is widely dispersed across sectors, the application of policy measures to influence its development in a certain way becomes very complicated, if not impossible. This might be especially true for nanotechnology related to concerns about consumer safety (Meyer 2007) – a policy measure introduced to improve consumer safety concerning nanotechnology applications in the food sector may prove to be counterproductive for nanotechnology enabled electronic devices. It is the widespread use of the GPT which makes a one size fits all policy inappropriate (Genet, Errabi, and Gauthier 2012). Third GPTs are said to play a major role in economic growth. By incorporating GPTs in economic models it is not only possible to explain growth endogenously but also to generate an integrated model of growth and business cycles (Bresnahan and Trajtenberg 1995). This underlines not only the qualitative differences of GPTs compared to non-GPTs but also the quantitative aspects. Summing up, it is the feedback effects, the lack of a one-size-fits-all R&D policy as well their high economic impact which make GPTs a field of study for its own.

But how are these aspects reflected in the evolution of the respective GPT innovation networks? Due to their wide applicability, GPTs may show a significantly higher degree of interdisciplinarity, leading to more intense or even new connections between existing fields of knowledge. For the case of nanotechnology its interdisciplinary nature is widely accepted, i.e. nanotechnology research draws its knowledge from a wide range of disciplines (Porter and Youtie 2009) as it can for instance be applied in different sectors such as biotechnology and ICT. The connections across sectors not only reflect the interdisciplinary nature but may also provide the pathways for repeated collaboration, which in turn may lead to innovation. However, these links are also bridges allowing knowledge inherent in one sector more easily spreading to another sectors. The innovation network of a GPT therefore can considered to be a network connecting other, already existing or evolving innovation networks. These networks in turn are affected by the GPT but still have their characteristics. For instance, Genet et al. (2012) state, that the knowledge transfer between large firms and research institutes seems to play a bigger role in nano-electronics than in nanobiotechnology, where small and medium sized companies hold more central positions. Thus, nanotechnology innovation networks may not only have their own characteristics and evolution trajectories, they also connect networks with different structures, thereby influencing their evolution and getting influenced by these. More general, GPT innovation networks can be considered to have significantly different characteristics from 'standard' technology innovation networks.

4 THE GPT SKIN MODEL

4.1 GPT innovation networks in SKIN

In the SKIN model (Simulating Knowledge dynamics in Innovation Networks; for more detail see (Ahrweiler, Pyka, and Gilbert 2004) heterogeneous agents optimise their innovation performance by improving its knowledge base under a constantly changing environment. Important aspects of innovation such as uncertainty, path-dependence, evolution of knowledge and learning, both by individual research as well as learning from partners, are already incorporated in the model. With the ability to simulate the emergence and evolution of innovation networks, the SKIN model also simulates an important artefact of innovation in knowledge intensive industries such as ICT or biotech. In these industries, networks are formed in order to create new knowledge by combining different technological and economic capabilities (Pyka 2002). However, the structure and evolution of general purpose technologies show some distinctive characteristics which a GPT SKIN has to be capable of reproducing.

Besides innovation networks representing the application sectors of the GPT, also GPT networks have to be incorporated in the model. Based on the wide-ranging applicability, GPT on the one hand should form a GPT innovation network, representing the idea of the GPT as a technology, which is also evolving by R&D on the GPT knowledge. Within nanotechnology, this could be found in the evolution of nanotechnology instrumentation. On the other hand, the GPT network has to show ties of various strengths to all its application sector networks. This is representing the combination of GPT knowledge with complementary knowledge being located in the application sector innovation network. Thus, one should be able to identify different sub-networks (application sectors) as well as a GPT network connecting the sub-networks.

By connecting various innovation networks, the GPT network also has a bridging function, allowing knowledge available in one application sector network to spread easily via the GPT network to other application networks. In the case of nanotechnology this phenomenon can be found in the empirical fact of nanotechnology companies applying their knowledge in various sectors (Meyer 2007). Due to their widespread applicability, agents having capabilities in the general purpose technology should be found within a broad range of application technology innovation networks.

The innovation triggering effect of a GPT and thus its important role for economic growth may also be reflected in the evolution of innovation networks. Prior to the applicability of the GPT within an application sector network, the respective network might show an evolution according to life-cycle theory with decreasing innovative activity in later stages of the life cycle, which could be reflected in a decomposition of the innovation network. At this stage, the network disintegrates because it has served its purpose and advantages in production costs become more important than the access to new knowledge (Schön and Pyka 2012). By applying GPT knowledge in this sector, new technological possibilities become viable, thus innovation activities will be revived and networks structures regain importance. Thus, the dissemination of GPT knowledge throughout various application sectors will not only trigger new innovations but should also be reflected in a reconfiguration of the application sectors innovation network.

4.2 Building Blocks of the General Purpose SKIN

To adapt the basic SKIN model in order to simulate the evolution of GPTs, it is necessary to change various building blocks already existing in the model.

In order to reflect the fact that there are application sectors where the GPT is applied an a GPT sector in which the GPT is developed, a subset of agents of several types will be created of which a few will be mentioned. The model will contain small and medium sized companies (SMEs) active in the application sectors and in the GPT sector. GPT SMEs however differ in the fact that they cannot sell to end-users and they are able to collaborate with more divers than other SMEs. Agents providing research infrastructure (RI) are important in nanotechnology and are thus included in the simulation. The participation of a RI in a network might for example increase the probability of success of the network's products. Also, RIs will have only a very restricted knowledge base, which is however unique and combined with a large capital stock.

With the learning and collaboration procedures another important building block of the SKIN will be adapted in order to capture the distinct characteristics of GPT innovation networks. There are several ways forms of learning implemented in the model: incremental and radical learning, adaptation to the needs of users, and leaning from other agents by co-operation and networking. Based on Argyris and Schön (1996), learning procedures implemented in the model can be categorized into single-loop and double loop learning. The first category includes learning by doing/using (agents use their knowledge and thereby increase their experience), learning by feedback (successful products generate revenue and are thus produced and kept in production), incremental learning (when market feedback is not satisfactory agents change their capabilities incrementally by research) and radical learning (when market feedback is not satisfactory but the agent does not have sufficient funds for incremental research). Double-loop learning is reflected in the possibility to forget (knowledge space is cleaned up), to individually change their learning strategy (chose between radical and incremental learning) and to collaborate (by co-operating and forming networks) (Ahrweiler, Gilbert, and Pyka 2011).

Learning and collaboration in the GPT SKIN however does have some special characteristics which, when implemented properly, should help replicating GPT innovation network evolution. First, collaboration between agents of different networks should be relatively sparse, as is for example between the electronics and pharmaceutical industry. However, with the emergence of the GPT, much stronger connections become established as the GPT can serve as a bridging technology. Thus, GPT agents will show more connections to different parts of the network, especially connecting technologically distant sectors. GPT knowledge will be able to spread via these bridges from one application sector to another. Second, SME GPT can be considered to learn differently from a larger GPT agent (Avenel et al. 2007). While small GPT agents move through the knowledge space by improving their knowledge base but keeping its size, larger GPT agents often add new GPT knowledge to their knowledge base without forgetting.

In order be able to see how the application knowledge and the GPT knowledge evolves and spreads throughout the system and to be able to model learning processes in a more evolutionary way, the next chapter will introduce the application of GAs in the SKIN model.

5 SIMULATING GENERAL PURPOSE TECHNOLOGIES IN SKIN WITH GENETIC ALGORITHMS

5.1 Building blocks of Genetic Algorithms

The idea of genetic algorithms dates back to Holland (1975), who introduced the idea to model biological evolution, and was first used in economic modeling by Birchenhall (1995) and has found much interest from scientists interested in the modeling of evolutionary economic systems (Geisendorf 2010). With GA it is possible to model the distribution of knowledge as well as its incremental and distributed change (Birchenhall 1995).

A GA model incorporates several building blocks which are the representation of knowledge as a sting of binary code, the recombination and mutation of these strings and internal as well as external selection mechanisms. In the following, crossover and mutation, and the selection mechanisms will be outlined in more detail in order to show their implementation in the SKIN model.

As Geisendorf (2010) argues, in order to reflect the difference between biological evolution, which is only determined by external selection, and economic evolution internal selection mechanisms have to be incorporated in the model. Internal selection mechanisms reflect the purposeful change of the genetic algorithm by incremental learning. At the same time, internal selection mechanisms fulfill various other aspects important for evolutionary modeling. They reflect the fact that "the actual reasons for economic success are not necessarily identical with what some economic agents believe to be the reasons" (Geisendorf 2010, p. 819), i.e. market feedback will not simply lead to a random incremental change in the genetic code but will be guided by internal selection. The fact that internal and external selection will not necessarily lead to the same result reflects the idea of incomplete information and bounded rationality (Geisendorf 2010), both of which are central concepts of evolutionary economics (Dosi and Nelson, 2010).

Mutation is referred to as being a stochastic element in R&D which leads to new knowledge, while the crossover operation recombines existing knowledge and is thus being seen as the most important genetic operator (Gilbert and Troitzsch 2005). Both operators are essential to be able to model endogenous economic evolution (Geisendorf 2010) and are used to create offspring chromosomes of two parent chromosomes. With crossover, both parent chromosomes are broken into two or more parts at randomly chosen points. The parts and are rejoined to create new chromosomes containing parts of both parents, thereby preserving building blocks over the generations. With mutation, parts of the chromosome are changed in a random way at randomly chosen times (Gilbert and Troitzsch 2005).

As both operators are crucial for modeling evolutionary economic developments, they need to be implemented in the SKIN model of GPTs using genetic algorithms. With mutation serving mainly as a stochastic element, the likelihood of a mutation an its effect on the genetic code has to be defined in the model. The implementation of the crossover mechanism however is less simple. In order to reflect the idea of GPT knowledge being combined with complementary knowledge from the application sector, the definition of building blocks, which have to be passed on throughout the simulation becomes important. Braking points should be predefined in a way to have a part of the chromosome being referred to as the GPT part, and another part to be the application part. Both parts however will be subject to all operators of the genetic algorithm itself. This means both parts of the genetic code will evolve by mutation, crossover and incremental and radical change.

Within the SKIN model, external selection can be accomplished in a meaningful way by the market on which the product resulting from a new innovation hypothesis is sold. If there are other companies in need for the respective product in order to use it as an input factor for their own product or if there is an end user in need for the product it can be sold, thus generating revenue and feedback effects (se below). Internal selection however can be interpreted as being conducted by the firm to intentionally give the evolution of the gene sequence a certain direction. One possibility could be to chose by tournament selection out of the two new sequences generated by crossover the one which is closer to an already successful product on the market.

5.2 Learning Procedures in a Genetic Algorithm Based SKIN

Implementing GA in the SKIN model will have to allow for the same kinds of learning and cooperative innovation as currently available.

Learning by feedback can be implemented in a similar way as in the kene structure, where a firm simply keeps on producing an unchanged product whenever the product is successful on the market. If however, a product cannot be sold successfully anymore on the market, i.e. the genetic code of the product does not fulfill the requirements of the external selection mechanism, the firm will change the genetic sequence incrementally. This incremental change in turn has to be guided by internal selection mechanisms of the

firm. Radical research may be implemented by changing larger sequences of the genetic code, thus leading to entirely new characteristics of the code and affecting its fitness.
Double-loop learning within collaborations or networks will be implemented in the SKIN model by using the crossover operator. When two agents combine their knowledge, the genetic sequences they want to be used in the new product are broken up in a certain way (see above) and recombined. This leads to a new set of genetic codes, which are then selected by the internal and external selection mechanisms. The choice of the learning strategy of an agent is also implemented in the GA SKIN, which means that each agent can either change smaller parts of the genetic sequence or larger sections. However it could make sense to predefine by the type of the agent which part of the sequence he is capable of changing and at which scale.

5.3 Stylised Facts of GPT and Nanotechnology – Further Modelling Requirements

Besides the particularities of GPT innovation networks, the model should also be able to replicate other important stylised facts about the evolution of a GPT in general and nanotechnology in particular. One of the most important characteristic of GPT evolution is the productivity paradox. This phenomenon was first described by Robert Solow with the statement "You can see the computer age everywhere but in the productivity statistics." (Solow, 1987). However, several years after the introduction of computers, productivity rates rose. This was later explained for example by the need for developing complementaries which were necessary to make full use of the computer for example in data processing. The same effects could be identified for other GPTs. This important stylised fact should not be ignored an might be translated into SKIN in a very simplistic way, for instance by declining prices of nanotechnology products used in the application sectors.

As a more nanotechnology specific stylised fact the importance of research infrastructures (RI) should be implemented in the model. Nanotechnology research is said to require special equipment (Shapira, Youtie, and Carley 2008) thus nanotechnology innovations are often by researchers and innovators with access to those facilities. This could be translated into the SKIN model by a higher chance for innovation hypotheses to succeed when originating from collaborations or a innovation network in which some RI is included. Further conceptualisation is however required to determine whether the combination with a RI leads to a higher fitness when selected by the internal or the external selection mechanism.

6 CONCLUSION

With the proposed framework we wanted to propose an adaptation of the SKIN model which is capable of capturing the special characteristics of a GPT innovation network. GPT innovation networks differ from other emerging technology innovation networks in their structure, function and connectivity. Furthermore, the wide range of applicability of the GPT on the one hand makes these technologies especially important for economic growth but on the other hand poses special requirements on any policy measure. By not only adapting the agents and dynamics of the SKIN model to the special case of GPTs, but also by introducing GA in SKIN we are able to model the evolution of GPT knowledge, its dissemination as well as agents' learning mechanisms in a more sophisticated way than before. Taking also other stylised facts of GPT and nanotechnology evolution into account, the model will be able to show even better the difference of the evolution of GPT/nanotechnology innovation networks.

REFERENCES

Ahrweiler, P., N. Gilbert, and A. Pyka. 2011. "Agency and structure: a social simulation of knowledge-intensive industries." *Computational and Mathematical Organization Theory*, 17(1):59-76.

Ahrweiler, P., A. Pyka, and N. Gilbert. 2004. "Simulating Knowledge Dynamics in Innovation Networks (SKIN)." In *Industry and Labor Dynamics – The Agent-Based Computational Economics Approach*, Edited by R. Leombruni and M. Richiardi, 284-296. Singapore: World Scientific Publishing Co. Pte. Ltd.

Argyris, C., and D. A. Schön. 1996. *Organizational Learning II: Theory, Method and Practice*. Reading: Addison- Wesley.

Avenel, E., A. Favier, S. Ma, and V. Mangematin, V. 2007. "Diversification and hybridization in firm knowledge bases in nanotechnologies." *Research Policy*, 36:864-880.

Birchenhall, C. 1995. "Modular technical change and genetic algorithms." *Computational Economics*, *8*: 233-253.

Bresnahan, T. F. 2010. "General Purpose Technologies." In *Handbook of the Economics of Innovation,* Edited by B. H. Hall and N. Rosenberg, 761-791. Amsterdam: North Holland.

Bresnahan, T. F., and M. Trajtenberg. 1995. "General purpose technologies "Engines of growth"?" *Journal of Econometrics*, 65(1):83–108.

Dosi, G., and R. R. Nelson. 2010. "Technical Change and Industrial Dynamics as Evolutionary Processes." In *Handbook of the Economics of Innovation,* Edited by B. H. Hall and N. Rosenberg, 51-127. Amsterdam: North Holland.

Geisendorf, S. 2010. "Internal selection and market selection in economic Genetic Algorithms." *Journal of Evolutionary Economics*, 21(5):817-841.

Genet, C., K. Errabi, and C. Gauthier. 2012. "Which model of technology transfer for nanotechnology? A comparison with biotech and microelectronics." *Technovation*, 32(3-4):205-215.

Gilbert, N., and K. G. Troitzsch. 2005. "Learning and evolutionary models." In *Simulation for the Social Scientist*, Edited by N. Gilbert K. G. Troitzsch. Berkshire: Open University Press.

Holland, J. H. 1975. *Adaptation in natural and artificial systems*. University of Michigan Press.

Jovanovic, B., and P. L. Rousseau. 2005. General Purpose Technologies. In *Handbook of Economic Growth 1*, Edited by P. Aghion and S. Durlauf, 1181-1224. Elsevier.

Lipsey, R. G., C. Bekar, and K. I. Carlaw, 1998. "What requires explanation." In *General Puprose Technologies and Economic Growth*, Edited by E. Helpman, Massachusets Institute of Technology.

Lipsey, R. G., K. I. Carlaw, and C. Bekar. 2005. *Economic Transformations: General Puropse Technologies, and Long-Term Economic Growth*. Oxford: Oxford University Press.

Ludeña, M. E., J. Pérez, E. Fernández, A. Fischmann, and G. A. Plonski. 2008. Assessing innovation networks in nanotechnology. In *Proceedings of the IV. Globelics Conference 2008*, Mexico City, Mexico.

Meyer, M. 2007. "What do we know about innovation in nanotechnology? Some propositions about an emerging field between hype and path-dependency." *Scientometrics*, 70(3):779-810.

Porter, A. L., and J. Youtie. 2009. "How interdisciplinary is nanotechnology?" *Journal of nanoparticle research: an interdisciplinary forum for nanoscale science and technology*, 11(5):1023-1041.

Pyka, A. 2002. "Innovation networks in economics: from the incentive-based to the knowledge-based approaches." *European Journal of Innovation Management*, 5(3):152-163.

Pyka, A., and P. P. Saviotti. 2002. "Innovation Networks in the Biotechnology-Based Sectors." Discussion Paper No. 22, Institute for Economics, Universität Augsburg.

Schön, B., and A. Pyka. 2012. "A Taxonomy of Innovation Networks." FZID Discussion Papers No. 42, Forschungszentrum Innovation und Dienstleistung, Universität Hohenheim.

Shapira, P., J. Youtie, and S. Carley. 2009. "Prototypes of emerging metropolitan nanodistricts in the United States and Europe." *NBER Conference on Emerging Industries: Nanotechnology and NanoIndicators*. Cambridge, Massachusetts.

Solow, R. 1987. "We'd better watch out." *New York Times Book Review*, 36.
Youtie, J., Iacopetta, M., and S. Graham. 2007. "Assessing the nature of nanotechnology: can we uncover an emerging general purpose technology?" *The Journal of Technology Transfer* 33(3):315-329.

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