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Knowledge-generating efficiency in innovation systems: The acceleration of technological paradigm changes with increasing complexity

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ABSTRACT

Time series of US patents per million inhabitants show cyclic structures which can be attributed to the different knowledge-generating paradigms that drive innovation systems. The changes in the slopes between the waves can be used to indicate efficiencies in the generation of knowledge. When knowledge-generating systems are associated with idem innovation systems, the efficiency of the latter can be modeled in terms of interactions among dimensions (for example, in terms of university–industry–government relations). The resulting model predicts an increase in efficiency with an increasing number of dimensions due to the effects of self-organization among them. The dynamics of the knowledge-generating cycles can be analyzed in terms of Fibonacci numbers; successive cycles are expected to exhibit shorter life cycles than previous ones. This perspective enables us to forecast the expected dates of future paradigm changes.

1. Introduction

The explanation of economic change in terms of underlying mechanisms has been central to evolutionary economics (Nelson and Winter, 1982; Andersen, 1994). According to Schumpeter (1939), the development of the economy is based on continuous innovations. This is especially the case in the post-industrial stage when the proliferation of knowledge can be considered as an important source of consistent growth (Romer, 1986, 1990). Studying Japan, Freeman (1987) first noted that knowledge generation can only be economically successful if an innovation system is in place (as a retention mechanism). Lundvall (1988, 1992) and Nelson (1993) elaborated on the systems perspective in innovation studies. Porter (1990, 1998) abstracted from the national context by focusing on "clusters" of innovations that can be shaped differently in regional and/or national settings. Gibbons et al. (1994) distinguished between a knowledge-production paradigm in niches such as universities ("Mode 1") and transnational and trans-disciplinary knowledge production ("Mode 2") driven by communication across institutional borders. "Mode 2" was further elaborated in terms of university–industry–government collaborations such as the Triple Helix model (Etzkowitz and Leydesdorff, 1995, 2000).

Initially, the concept of an innovation system was developed with a focus on national systems of innovation. In later studies, the notion of smaller-sized innovation systems was introduced, such as regional (Braczyk et al., 1998; Cooke, 2002), sectorial (Breschi and Malerba, 1997; Malerba, 2005), technological (Carlsson and Stankiewitz, 1991; Carlsson, 2006), and corporate innovation systems at different scales (Granstrand, 2000). A national system of innovations, as in the case of Hungary, can also be comprised of a number of smaller regional systems (Lengyel and Leydesdorff, 2011). This concept of nested innovation systems was also proposed as a model for economic development at the city level (Etzkowitz and Raiken, 1980).

The systems perspective relates to the evolutionary one because a system is shaped when different selection mechanisms

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operate upon one another. Two selection environments can mutually shape each other in a coevolution along a trajectory, but adding a third sub-dynamic can cause a bifurcation and consequential transitions in the system at the regime level (Dosi, 1982). Ivanova and Leydesdorff (2014) argued that adding a third selection environment to a system established in terms of bilateral (e.g., university–industry) relations or bilateral (e.g., government–university) policies can drastically change the behavior of an innovation system because a third sub-dynamics provides an additional source of variation that continuously upsets previous tendencies toward equilibrium (Nelson and Winter, 1982). Note that this accords with Simmel's observation that the difference between social dyads and social triads is fundamental; this difference refers not so much to the number of participants as to more fundamental issues, such as the quality, dynamics, and stability of the resulting system (Simmel, 1950).

When referring to the innovation activity of a system, one can use the notions of the *capacity* and *efficiency* of an innovation system to distinguish among different systems and inform policy choices. Various quantitative methods in which input indicators are used to estimate output have been developed to evaluate the *capacity* of an innovation system. Cai (2011) categorized these methods into three categories: Composite (Innovation) Indicators, Data Envelopment Analysis (DEA), and Modelling/Econometric Approaches. The *efficiency* of an innovation system, however, is difficult to specify because of the complexity of and possible synergy among the innovation activities, such as investments in R&D, the numbers of new services and products, patents, and research (Hollanders and van Cruysen, 2008); adequate efficiency indicators are therefore difficult to construct. Another problem is that innovation statistics is still rather uncertain, which leads to stochastic fluctuations and consequently to difficulties in the estimation of parameters.

The efficiency of an economic system can be defined analogously to technical efficiency as the ratio of output to input (Farrell, 1957). An innovation system can be considered as efficient if it is able to produce the maximum possible output from a given amount of innovative input. Efficiency can then be defined by using the knowledge production function (KPF) with the number of patents as an output variable (Fritsch and Slavtchev, 2010; Schmookler, 1962) that can be written as a product of input variables (Griliches, 1979; Jaffe, 1989; Shelton and Leydesdorff, 2012). The input variables can be rather diversified, such as the level of R&D expenses, the number of R&D employees, or the state of the technological, industrial, and institutional infrastructures. However, one cannot include all the factors that influence the capacity of an innovation system because some of these factors cannot be measured. For example, the interaction among different elements of an innovation system may generate self-enforcing (auto-catalytic) systemic effects that affect the performance of the system (Leydesdorff and Fritsch, 2006).

When comparing innovation systems at the national or regional level, it is thus possible that two systems may perform unequally despite a set of equal input parameters, whereas one would theoretically expect a more equal efficiency. This discrepancy can be attributed to differences in the intensity and quality of the interactions in the systems under study. In other words, the analyst risks comparing non-comparable systems, such as systems of a different nature or with different structural organizations. The mechanism of self-organization, lying at the origin of biological complexity, can also be expected to provide system change in the economy (Tominomori, 2002) by generating more efficient and more sophisticatedly organized systems under selection pressure. In summary, one can expect to find a relation between the organizational efficiency of a system and the level of the system's self-organization.

Our research question is to explore (*i*) the influence of complexity in innovation systems on their knowledge-generating performance, and (*ii*) regularities in the improvements of the efficiency of the knowledge-generating system over time. To this end, we compare the measurement results with the maximal efficiencies that can be derived from a theoretical model. The analysis is pursued at the macro-level of the system. We use US patents as data for reasons that will be specified, but which also limit the validity of our conclusions to this domain.

The paper is organized as follows. In Section 2, the statistical patent data (USPTO) are analyzed; and four distinctly shaped cycles are distinguished during the period 1840–2013. These cycles partially coincide with the Kondratieff cycles. A model of the efficiency of knowledge generation in innovation systems is developed in Section 3. The model explains the empirical findings in considerable detail. One conclusion of this model is that the system's performance is proportional to the complexity of the system. In Section 4, we discuss the perspectives of extending the model to a next-higher dimensionality in order to specify expectations about changes in the driving knowledge-generating paradigms. In Section 5, the results are summarized, and policy implications are formulated in Section 6. The mathematical derivations for calculating the dimensionality of innovation systems are provided in two Appendices.

2. Data analysis using US patent data

The relations between input and output in innovation systems are no longer unidirectional because of feedback loops at the systems level. On the one hand, newly generated technologies can be considered as inputs to the total productivity together with the other knowledge carriers (Solow, 1957; Coe et al., 2009). The number of patents can, on the other hand, be considered as an indicator of the innovation capacity of a system (Fritsch and Slavtchev, 2006). Patents first reflect innovations in the databases for the purpose of legal protection of intellectual property. Furthermore, there is a correlation between the innovation capacity and a country's overall competitiveness and level of prosperity (Porter and Stern, 2002). Economic growth implies and is dependent on the growth of innovation efficiency. Patents have often been used as a simplification of innovation indicators (Jaffe and Trajtenberg, 2002). However, there is no one-to-one correspondence between patents and innovations. Only a small percentage of patents can be expected to be used in practice, and only a small percentage of those patents used can be expected to pass to the category of innovations. The drawback of using patent indicators is that they are very uncertain as numbers of innovation output (Romijn and Albaladejo, 2002). However, patents have been used as a measure of the intensity of innovation activity (Porter and Stern, 2002).