ARTICLE IN PRESS

Technological Forecasting & Social Change xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

General Purpose Technologies as an emergent property[☆]

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A R T I C L E I N F O

Keywords:
General purpose technology
Technology networks
Pervasiveness of technologies
Knowledge diffusion
Innovation

JEL codes:
C63
D83
D85
L16
O3

A B S T R A C T

We address the emergence of General Purpose Technologies (GPTs), the process which has been largely neglected in the literature on technological change. We do this from a novel network-based perspective emphasizing the relations between technologies and how combinations of those technologies form final goods. Transforming GPT emergence into a question of technology adoption we demonstrate that GPTs are more likely to emerge when certain conditions with regard to the following techno-economic factors are met: knowledge diffusion, concentration of R&D efforts and variation in the rank of expected returns on products. Focusing solely on a discovery process our model demonstrates an impressive fit to real data reproducing a number of stylised facts including technological lock-ins, S-shaped curves of technology adoption, temporal clustering of innovations and distinct features of empirical networks of relatedness among technologies and products.

1. Introduction

General Purpose Technologies (GPT) were introduced as one of the forces to explain economic growth and its cyclicality (Bresnahan and Trajtenberg, 1995; Bresnahan and Yin, 2010; Syverson, 2013). Ever since their wide acknowledgment in the book of Helpman (1998), they are seen as engines of the development of industries (Strohmaier and Rainer, 2016), whole countries (Ott et al., 2009), and as an explanation of the long waves theory (Devezasa et al., 2005; Schumpeter, 1939). " A GPT is a single generic technology, recognisable as such over its whole lifetime, that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many spillover effects" (Lipsey et al., 2005, p. 98).[1] We can observe the *pervasiveness* of electricity through vast amount of products and services using it, or the *technological dynamism* of semiconductor industry in the last century reflected in the ' Moore's Law', or the *complementarity in innovations* when the evolution of ICT sector has led to the introduction of numerous new products and services (like personal computer, internet, GPS) that spurred even more innovations in virtually every industry. But how does it happen that a technology becomes so powerful?

In the early GPT models, the emphasis was on the attempt to account for a ' residual' in aggregate production functions of mainstream neo-classical models (Bresnahan and Trajtenberg, 1995; Helpman, 1998) and explain the famous ' productivity paradox' (Brynjolfsson, 1993) or demonstrate the evolution of a GPT "under a stream of innovations" and the effect of a newly arrived GPT on the economy (see also Carlaw and Lipsey, 2006). More recent models on GPT focus on a ' dual inducement mechanism' between GPT and its application sectors (Bresnahan, 2012) assuming one in a pair of complementary technologies to have generality of purpose. Taking the appearance of a GPT for granted these works elaborated on ' growth bottlenecks' (Bresnahan and Yin, 2010) arguing that there are types of knowledge that lead to significant advancements. In contrast to these models, where a GPT "arrives from the outside of the system" (Cantner and Vannuccini, 2012, p. 74), we shift the focus from the effect which GPTs have on economy to its emergence.

We acknowledge that a knowledge landscape is heterogeneous and innovation process is non-deterministic. Our work builds on the literature started by Schumpeter (1934, p. 65) defining innovations as "new combinations" of new or existing knowledge, and continued by theories of architectural innovation (Henderson and Clark, 1990), recombinant growth (Weitzman, 1998), combinatorial technology models

☆ Financial support from the Helmholtz Association (HIRG-0069) and Projex CSES, Initiative d'Excellence, Université de Strasbourg. Thanks are due to the very helpful comments and suggestions from Robin Cowan, Patrick Llerena and Ingrid Ott. This work has benefited from presentations at workshops in Jena, Karlsruhe, Bochum, Strasbourg, Essen, Pisa and Zurich as well as from CEF conference in Bordeaux and ISS congress in Montreal. Suggestions of two anonymous referees are acknowledged. All remaining shortcomings are our responsibility.
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[1] The work of Lipsey and Carlaw names eleven characteristics of GPTs and provides a comprehensive overview (Carlaw and Lipsey, 2011).

https://doi.org/10.1016/j.techfore.2017.12.011
Received 9 August 2017; Received in revised form 11 December 2017; Accepted 17 December 2017
0040-1625/

Please cite this article as: Korzinov, V., Technological Forecasting & Social Change (2017), https://doi.org/10.1016/j.techfore.2017.12.011

(Arthur and Polak, 2006) and works on technological capabilities (Hidalgo and Hausmann, 2009) considering knowledge as a collection of heterogeneous pieces that have hierarchical structure and are interrelated (Lipsey et al., 2005).[2] Instead of relying on the concept of aggregate production function which does not allow to reveal the differences in knowledge characteristics, we capture knowledge heterogeneity by its network structure offering a novel perspective on the knowledge discovery process as a network growth. In particular, if links between technologies represent a *capability to combine them in a product that has an economic value*, then a potential of a technology to become a GPT must be supported by its central network position.[3] Concentrating solely on the pervasive property of GPT, the process of its formation transforms into inclusion of a single technology into as many goods as possible. Technically this is achieved by modelling the technology to have the *potential* to be included in all final goods, but without *certainty* to do so due to multiple alternative ways of producing the same type of good. Accordingly, we consider the emergence of a GPT not as a binary but a continuous outcome, where certain technologies may exhibit the pervasive property to different extents, and the larger this extent the more likely the technology is classified as a GPT.

Methodologically we resort to a numerical (simulation) analysis due to the complex network structures and the stochastic nature of the discovery process, thus, making our work similar to Arthur (2005), Cowan and Jonard (2009), Silverberg and Verspagen (2005). Practically speaking, we generate a large graph of possible technological combinations where each technology has a certain potential ability to be utilised in a certain number of final goods and look for a minimum set of (techno-economic) conditions that foster or hamper a GPT formation. To support our modelling assumptions, we replicate some known stylised facts (such as S-shaped curve of technology adoption, temporal clustering of innovations in time and some distinct features of networks of the product and technology relatedness discussed by Hidalgo and Hausmann (2009) and Boschma et al. (2014)) concluding that the close similarity of the model's output to reality shall indicate the similarity of forces producing them.

Among the usual suspects we outline the process of knowledge diffusion, the structure of the technological network, the choice over technological trajectories to follow and the pressure from the demand side in discovering new products. Knowledge diffusion is considered because of its public good property (Arrow, 1962) and the resulting possibility to create “complementarities among trajectories”[4] (Dosi, 1982, p. 154). The extent of this effect, however, is contingent on the exact network structure of knowledge, since the complex interrelationships between technologies can result in some technological combinations being part of numerous products or very few only. Another rationale to consider the knowledge network is that the potential GPT is not necessarily the only technology having large scope of applications, but that all technologies have a different potential degree of pervasiveness thus affecting each other's chances to become adopted. The mechanism behind choosing between technological trajectories, in its turn, is important due to the competition among the aforementioned alternative technological combinations in becoming first to satisfy each consumer need as well as the fact that the innovation process must be seen as a search in complex technology spaces “shrouded in uncertainty” (Silverberg and Verspagen, 2005, p. 226) and characterised by strong path dependence (Nelson and Winter, 1982). Finally, the role of the demand side is not clear. Is it beneficial for the knowledge discovery process in general and the GPT formation in particular that society starts favoring a certain product development as it was the case, e.g., for nuclear power plants in the 1950s (Cowan, 1990) or renewable energy generation in the last two decades (Herrmann and Savin, 2017)? In both cases, the policy maker was providing large subsidies to discover a product with certain characteristics, while future payoffs of those technologies were very uncertain. Clearly enough, none of the four factors shall be considered in isolation from the others, and the rest of the study devotes particular attention to the interplay between those forces.

Our results demonstrate that the knowledge diffusion consistently supports the GPT emergence since being discovered once the knowledge spills over and becomes applicable in many other products benefiting most those technologies with higher degree and used for production of different final goods. These benefits are better appropriated the larger the gap between those leading to goods produced with the GPT and those without it. Given the presence of knowledge spillovers, concentration of R&D efforts on technological trajectories where more knowledge is already accumulated also favors GPT in the short term. However, once the technology network is modelled as a growing construct where agents become aware of more complicated technological combinations through inventing simpler products, the effect of concentration of efforts transforms into an inverted U-shape form. For the same reason, volatility in demand has a negative effect on GPT's formation: if different products become very lucrative in different periods of time, the size of discovered technology network shrinks, limiting the resulting knowledge diffusion and leading to a technological lock-in. Important to stress is that in contrast to the existing literature abovementioned, the emergence of GPT is neither necessary to be modelled exogenously nor does solely depend on ex ante higher expected profits (Bresnahan, 2012), but can be addressed in the novel network-based technology adoption framework presented in the following. Providing this framework that simultaneously comprises the role of knowledge diffusion, demand and firms strategies with respect to which technological trajectories to follow is, in our view, the main contribution of this study.

The rest of the paper is organised as follows. Section 2 describes the basic setup of our model and formulates four propositions on factors triggering the process of GPT adoption. We provide results of the numerical analysis of our baseline model in Section 3 additionally extending it by introducing an increasing in time knowledge base. In Section 4 we outline some stylised facts that our study reproduces, while Section 5 discusses implications of the results and concludes.

2. The Model

2.1. Technology network

In this model we focus on the process of knowledge discovery. In particular, it is assumed that to satisfy consumer needs, certain population of product types (P) is necessary to be discovered (innovation as a problem-solving process). For this purpose, some intermediates (I, which in reality are typically combinations of other intermediates) need to be combined. We simplify our modelling by considering only two layers (see left panel of Fig. 1): the product types (final goods) and the intermediates (technologies used to produce the intermediate input: screw press, combustion engine or laser).[5]

From the beginning, the technologies are present in the model as yet

[2] While in reality a complex technology can consist of sub-technologies, which in their turn consist of sub-sub-technologies and so on, we simplify this modular structure implying final goods to be producible out of a large group of interconnect-able but single technologies. Note that this is done without loss of generality since those complex technologies can be seen as interconnected groups of intermediates, which in their turn have to be all connected to further technological inputs to invent new final goods.

[3] Thanks to one of our referees, we became aware of another study, namely Masson et al. (2017), relating technology generality to the interdependencies between technologies. However, while in Masson et al. (2017) a GPT is designed purposely, we test the role of external factors on GPT adoption.

[4] What is meant is the possibility to utilise the same knowledge in more than one technological area. A good example is a screw press (which is a combination of screw and wheel or handle) borrowed by Gutenberg from wine makers in the Rhine area and applied to printing press (Johnson, 2010).

[5] Henceforth, we use the terms ‘technology’ and ‘intermediate’ as synonyms.