## Knowledge discontinuities, obsolescence and the rate of technology performance improvements

## Introduction

Economic theory has identified technology as a key source of growth. Access to technology vintages of different quality can explain productivity and growth rate differentials across countries (e.g. Solow, 1957; Lucas, 1988; Romer, 1990; Rebelo, 1991; Fagerberg 1994, 1997 and 2000; Fagerberg and Vespagen, 2002; Verspagen, 1991). Technology improves through sequences of inventions, which, in their essence, are engineering, or scientific ideas or combinations of both. If we want to understand the fundamental long-term drivers of economic growth, we need to identify the sources of technology improvements. Technologies improve at different rates, with some technologies whose performance persistently improves faster than others (Magee et al., 2016; Nagy et al., 2013). Why is that so? Benson and Magee (2015) showed that the number of forward citations received by patents belonging to a technology domain<sup>1</sup> within the three years from their grant date, and immediacy of their backward citations (i.e. the average grant year of the patents they cite) are predictive of the rate of performance improvement in a domain. This empirical observation suggests that technology domains in which the technical knowledge becomes rapidly obsolete are those that experience faster rates of improvements. This can be explained by a more frequent arrival of important innovations, which shows new and better ways of solving the engineering challenges related to the given technology and speed up technology improvements. In this work, we define a method to empirically identify discontinuities in engineering design trajectories and estimate the knowledge obsolescence rate in a technology domain using patent data. We then test the hypothesis that faster rates of technology performance improvement in a technology domain are associated with a higher number (or more frequent arrival) of knowledge discontinuities in its engineering design trajectories and with faster rates of knowledge obsolescence. We use patent data and technology performance data for a set of 28 technology domains (such as integrated circuits, 3D printing, genome sequencing and solar photovoltaic) to test this hypothesis. The set of relevant patents for each domain has been retrieved by Benson and Magee (2013) using a hybrid classification and keywords method.

## Methods

We identify changes in engineering design trajectories (also known as knowledge discontinuities) by using a method that measures the path-changing content of patents and identify emerging technology subdomains developed by Triulzi (2015). The method is able to disentangle complex patent citation networks and identify, with statistical significance, patents that preferentially improve on previously poorly exploited prior inventions (Fig. 1A). This is interpreted as an instance of wider search across the space of possible design solutions. More discontinuities leads to faster knowledge obsolescence in the technology domain. We estimate the obsolescence rate by fitting a Weibull curve to the probability that a patented invention will receive citations as a function of its age (Fig.1B). The parameters of the Weibull curve can be used to measure the speed of diffusion and rate of obsolescence of technical knowledge:

$$p(age \mid k, \lambda) = \frac{k}{\lambda} \left(\frac{age}{\lambda}\right)^{k-1} e^{-\left(\frac{age}{\lambda}\right)^{k}}$$
obsolescence =  $\frac{1}{k\lambda}$ 

<sup>&</sup>lt;sup>1</sup> The set of patents belonging to a technology domain was identified by the authors using a technology classification overlapping method based on an initial keyword and key company search. The method is discussed in Benson and Magee (2014 and 2012).

We then investigate whether domains with more frequent arrival times and faster obsolescence have faster performance improvement rates. We use technology performance data made available by (Magee et al., 2016) and Nagy et al. (2013).





This work not only provides new methodological tools to the tech-mining community, but also contributes new theoretical insights on technology development. Our main hypothesis is an alternative possible explanation of improvement rate differentials across technologies from that given by Basnet and Magee (2016). This alternative explanation is that different arrival rates underpin the fundamental drivers of technology performance improvements. Whereas Basnet and Magee's model treats the fundamental drivers of rate differences to be involved with the ability of a domain to takeup and convert widely available ideas to performance improvement. We hypothesize that higher technological competition in a domain pushes firms to differentiate their search strategies in the technology landscape and explore new technology design trajectories. This leads to a larger appearance of knowledge discontinuities. To disentangle the intrinsic endogeneity we estimate a structural model similar in its spirit to the famous R&D-Innovation-Productivity model developed by Crepon, Duguet and Mairess (Crepon et al., 1998). The model has three equations, one estimates the arrival rate of discontinuities as a function of competition, a second one uses the predicted arrival rate as an input of an equation that estimates the predicted obsolescence rate, which is then used to predict the rate of technology improvements.

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