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“Editorial: Big Data and Network Analysis in National Innovation Systems (NIS)”

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1. INTRODUCTION

The practice of innovation policy has changed significantly over the past forty years (Chaminade et al., 2012). Early discussions on how to foster innovation in regions or countries tended to emphasise the role of investment in R&D in line with the linear model of innovation (Schot and Steinmuller, 2018). This model of innovation policy clearly showed its shortcomings (both intellectually and practically) when it failed to explain why increasing investment in R&D did not necessarily translate into a competitive advantage and why large, developed economies were not on the innovation frontier despite hosting R&D intensive companies (Chaminade and Edquist, 2006). As a result, innovation policy started to emphasise the importance of the systems approach where networks of institutions and agents play an essential role to explain the diffusion of knowledge (Lundvall, 1988; 2010; Chaminade et al., 2009). The innovation systems approach highlights that different agents (i.e. not only businesses) are involved in innovation production, but they do so with different objectives and goals (Chaminade et al., 2010). The assumption is that relationships between companies and research centres multiply the diffusion of innovations and the competitiveness of a country or an economic system (Lundvall, 2007). The concept of innovation systems has been hugely successful in policy circles, and mostly because of its applicability; as a result, innovation policy has become intertwined with the innovation systems approach in several countries [1] (Chaminade et al., 2009). The importance

[1] OECD (2015). Of course, this process has not been straightforward: the old paradigm still survives, and it is not uncommon to find references to it in policy documents that explicitly claim to adopt an innovation systems approach.

of the innovation system paradigm has been highlighted in the literature (Nelson, 1993; Patel and Pavitt, 1994, 1997; Lundvall, 2007).

Academically, innovation systems (and their strength and weaknesses) have been widely discussed.[2]; however, we still have questions on innovation systems: how do innovation systems emerge? What is the role that individual agents' strategies play in such a process? Past research has highlighted the importance of entrepreneurs in creating conditions for the emergence of innovation systems; still, several authors have emphasised the importance of policy interventions for this purpose (Chaminade et al., 2019; Grillitsch et al., 2019). In other words, we do know not yet what creates a successful innovation system.

One of the shortcomings of the literature on innovation system is that it is mostly qualitative and difficult to generalise.[3] However, Phillips and Linstone (2016) suggest that describing the interactions among different agents in an innovation system requires an abstract representation of the system. Complex systems can be such a representation as they are characterised by a multiplicity of agents' interactions and heterogeneity (Arranz and Arroyabe, 2009). In this context, Phillips (2008) and Phillips and Linstone (2016) suggested that innovation systems require new methods rooted in Big Data Analytics and Network Analysis and neo-evolutionary methodologies such as Agent-Based models

As the capability to capture and store data has improved dramatically over time, Big Data's concept has so become relevant to the analysis -and to some extent, modelling- of innovation systems. In this context, the critical question is: can Big Data help us understand what drives the emergence of innovation systems and their performance? Can it help researchers and policy-makers identify features of innovation systems that have a non-obvious bearing on their performance? With this Special Issue, we try to answer these two questions.

2. Innovation Systems: a Short History

[2] See Lundvall (2007, 2010), who has analysed theoretically the concepts underlying the innovation systems and the work of Watkins et al. (2015), who have critically reviewed the literature on innovation systems starting from the macro approach up to meso- and micro-level.
[3] A remarkable exception is Leydesdorff, L. & Park, H.W. (2014), who have tried to measure a synergy within the National Innovation Systems in terms of the Triple Helix.

The concept of “innovation system” was developed by Lundvall in his theory of innovation as an interactive learning process (Lundvall, 1988). However, several authors have provided several alternative definitions. For instance, Nelson (1993) defined a National Innovation System (NIS) as a system where public and private sectors generate knowledge. Freeman used the innovation system as an analytical device to understand why some economic systems behave better than others in terms of innovation (Freeman, 2002; Freeman and Louca, 2001). In all cases, the emphasis is no longer on the single firm investing in R&D but on multiple agents and networks contributing to the innovation process (Lundvall et al., 2002).

The concept of innovation system has also been adapted to regional economies, and it has led to the concept of a regional innovation system where geography matter in a particular way to help share tacit knowledge (Saxenian, 1994). Regional policy has extensively used the concept of regional innovation systems as a tool to promote local economic growth: for example, the concept of regional innovation system underpins the EU's Smart Specialization framework. Another variation of the innovation system concept is the technological innovation systems that focus on networks, institutions, and technologies interacting in a specific technological field, and so it supplements the traditional notion of innovation systems.

3. Big Data

The volume of data generated by businesses, government, third sector and individuals has increased enormously (Dedic and Stanier, 2016). The growth of the Internet and the number of devices connected to it have generated a massive amount of data, and such exponential increase has led to the term "big data".

Laney (2001) characterises big data using 3V's. The three V's represent volume, velocity and variety. Volume is the size of the data that businesses generate from various sources such as social media, business transactions and the Internet. The second V (or velocity) refers to the speed at which data is collected. Finally, the third V refers to the variety of formats big data can be. Big data can be semi-structured, structured or unstructured (Dobre and Xhafa, 2014). Although big data exists in various formats, unstructured data is the most common type of big data generated by sensors, smartphones and social media networks. In the case of unstructured data, deriving meaningful insights in an automated way may require new techniques rooted in data science or analytics. Data analytics (or data science) is a term that has gained in popularity over the last ten years (Omar et al., 2017), and sometimes, they are used as synonyms. However, while big data refers to the characteristics of data captured by different devices or software (like sensors or web-sites), data analytics is the label for the methodologies that enable to analyse big data. Analytics relies on quantitative methods such as statistics, econometrics, machine learning, and network science. Additional methodologies include social media analytics, video and audio analytics and text analytics (Gandomi and Haider, 2015).

Can Big Data help improve the performance of innovation systems? The classical approach to measure performance of the NIS uses innovation output (such as the number of patents or publications), combined with the innovation inputs, such as skills or R&D expenditure. However, if innovation systems are complex systems, one needs additional measures to account for the system dynamics and evolution. In this sense, analytics and big data provide an opportunity by creating new indicators and novel methods of analyses. This approach allows measuring the innovation potential of organisations, defined by their technological capabilities.

Recent advances in Network Analysis have rationalised the linkages among agents as networks that act as "highways" for information exchange. Modelling a NIS as a complex network through the application of network analysis tools would allow the examination of network properties and their effect on the overall performance of NIS and the performance of individual actors in it. Hence, network analysis application to innovation systems would allow analysing cooperation patterns involving universities, companies, and the public sector. A network analysis approach can also help us understand the evolution of networks. Several authors (Zuking and DiMaggio, 1990; Ruef et al., 2003; Grenwal et al., 2006) have highlighted concepts of network embeddedness and social capital as crucial drivers of the performance of actors that make up the network.

Network analysis can explain why knowledge may not flow among agents (Woolthuis et al., 2005). These problems refer to nature as well as the intensity of such linkages. Strong ties can help knowledge transfer, but the organisation cannot critically assess the acquired knowledge if these are too strong. If the ties are too weak, then an agent may not be aware of the knowledge produced by other organisations in the innovation system. That can result in a slowed down innovation process. Finally, lock-in problems may emerge if firms are not aware of emerging technologies. If the whole innovation system is specialised in a particular technological field, then the whole system can be locked-in and firms in the system may not take advantage of new technological opportunities.

It is worthwhile noting that systemic problems give rise to opportunities for policy interventions. Indeed, knowledge does not flow well in the system, and therefore, the development of innovation is overall hindered. Of course, because policy-makers may have limited information on how the innovation system works, Big Data's availability can help policy-makers learn about the innovation system's behaviour and improve their interventions.

4. This Special Issue

This special issue comprises eight papers that have used analytics to understand the innovation systems' critical features in many countries. Using data from the Global Innovation Index, Mariuccia et al. (2020) show how to use Social Network Analysis to study the relationship between the Quintuple Helix and System Dynamics modelling. The suggestion is that identifying systems' structural features through Network Analysis can provide information on an innovation system's properties. This approach can be particularly relevant to policy-makers as it allows us to identify levers to amplify the impact of specific interventions on the innovation system's performance. Arranz et al. (2020) have also used Social Network Analysis to explore the UK's nanotechnology research collaboration network. The work starts from the traditional university-industry–government three-helix interaction model, but it crucially shows that international collaboration and non-profit organisations have become quite important in knowledge generation. Hence the need to update current models of innovation systems so that emerging features are included in them.
Similarly, Arroyabe et al. (2020) have used social network analysis to describe the Agri-Food network's topological properties funded by the Framework Programme between 2008 and 2014. The analysis shows that the effectiveness of innovation systems depends on the participants' heterogeneity and geographic diversity and their position in the network. Notably, the analysis highlights the importance of the structural properties of the network underlying an innovation system.

What benefits accrue to firms that are part of innovation systems? Seung-Pyo et al. (2020) have analysed the impact of public-private innovation networks (PPIN) on participating in SMEs' performance in Korea. They focus on three performance measures (namely sales, liabilities and R&D investment) and use a machine-learning ensemble model to model the relationship between performance and PPIN participation. The results suggest that, while joining a PPIN does not impact sales and liabilities, it is positively correlated with the R&D investment. In other words, innovation networks can stimulate R&D investment at the firm-level, but this does not necessarily translate into improved business performance because of the lag between R&D investment and the subsequent development of new products, increasing sales. Mavi and Mavi (2020) focus on eco-innovations and their drivers in the EU innovation system. From a methodological point of view, the authors show how to uses Data Envelopment Analysis to analyse innovation systems.

Innovation systems require knowledge to be shared among the economic agents. Sengupta and Sena (2020) have analysed the dynamic consequences of two different approaches to knowledge using a complex adaptive systems approach. The first approach assumes that firms are willing to share their knowledge and technology for free, while the second approach assumes that knowledge can be exchanged following a fee's payment. The analysis suggests that firms that share knowledge freely among themselves are more profitable than those operating under the second approach. Consumer preferences matter in both cases. When consumers speedily purchase new products, the industry concentration increases quickly while the overall technological progress rate slows down.

Finally, we focus on innovation systems that are geographically bounded. Yao et al. (2020) investigate innovation in cities. Adopting a social network lens, they argue that a city's innovation performance hinges on its centrality in intercity co-invention networks. Using a longitudinal data set of patents in China, they study the formation of an intercity innovation network within China's national innovation system. The study confirms that innovation is enhanced when cities are deeply embedded in innovative intercity networks.

Our wish is for this special issue to develop an interest in the topic. Besides, we hope this special issue will offer innovation policy-makers some guidance to assess the conditions under which Big Data exploitation can add value to innovation policy-making.

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