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Local and Non-Local Knowledge Typologies: Technological Complexity in the Irish Knowledge Space

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Abstract

It is now commonplace to assume that the production of economically valuable knowledge is central to modern theories of growth and regional development. At the same time, it is also well known that not all knowledge is equal, and that the spatial and temporal distribution of knowledge is highly uneven. Combing insights from Evolutionary Economic Geography (EEG) and Economic Complexity (EC) the primary aim of this paper is to investigate whether more complex knowledge is generated by local of non-local (foreign) firms. From this perspective, a series of recent contributions have highlighted the role of foreign firms in enacting structural transformation, but such an investigation has yet to account for the complexity of the knowledge produced. Exploiting information contained within a recently developed Irish patent database our measure of complexity uses a modified bipartite network to link the technologies produced within regions, to their country of origin *i.e.* local or non-local. Results indicate that the most complex technologies tend to be produced in a few diverse regions. For Ireland, our results indicate that the most complex technologies tend to be produced in a few diverse regions. In addition, we find that the majority of this complex knowledge is generated in technology classes where the share of foreign activity is greater than local firms. Lastly, we generate an entry model to compute the process of complex regional diversification. Here the focus is on how regions develop a comparative advantage in a technological domains more complex than those already present in that region. As such, we focus our attention only on those technologies with the highest complexity values, as these technologies are said to underpin the European Union's Smart Specialisation thesis.

Keywords: Relatedness, Technological Complexity, Diversification, Knowledge Space, Smart Specialisation, Ireland.

1) INTRODUCTION

For economic geographers, the enduring importance of geographic proximity in meditating knowledge flows is an oxymoron. Why is it, that despite advances in communication technologies and transport technologies that geographic proximity still matters? Or that, despite the ease of technology transfer certain regions have remained the epicentre of innovation while others have either failed to catch up or fallen behind? One particular claim is that a number of "geographical biases" lie at the root of regional development (Boschma, 2017). At the regional level, these biases reflect organised communities of practices (Malmberg and Maskell, 2006), untraded interdependencies (Storper, 1995) and institutional arrangements (Bathelt and Glückler, 2013) all of which contribute to – and reinforce – a series of place-based assets. Unravelling these biases has become a focal point throughout regional studies as it reveals the complex geo-centric processes that lie at the heart of knowledge creation and regional diversification (Boschma and Frenken, 2012).

It is true that advancements in communication technologies have enabled certain firms to lower their production costs and operate in a seemingly footloose fashion. But this is a cautionary tale, whose effects are not uniformly felt. In particular, the capabilities and inputs of technological sophisticated firms are more nuanced and complex. They compete on the basis of product differentiation and innovation (Feldman and Kogler, 2010). Differentiating between the two, distinguishes between firms that exploit codified knowledge *i.e.* ubiquitous and footloose, and firms that exploit tacit knowledge *i.e.* non-ubiquitous and spatially sticky (Gertler, 2003). Incidentally, as knowledge has become more complex and its production more specialised a premium will continue to be placed on physical interactions as tacit knowledge suffers from a steep distance decay (Howells, 2002; Boschma, 2005).

In this vein, a recent contribution by Balland and Rigby (2017) has suggested that not all types of knowledge are equal, drawing attention to the fact that certain technologies are more or less valuable than others. In doing so, the authors challenge a worrying tendency among economic geographers to merely focus on the quantity of knowledge inputs, without appropriately considering the quality of the knowledge produced. Following these insights, and with the development of more sophisticated databases several authors have begun developing more systematic ways at evaluating the value of new technological knowledge

(Quatraro, 2010; Kogler *et al*., 2013, Rigby 2015; Boschma *et al.,* 2015). Particularly influential in this regard is the emerging framework of technological relatedness (Whittle and Kogler, 2017), which has recently found residence alongside the writings of economic complexity (Hidalgo and Hausmann, 2009; Hidalgo, 2015) and the branching capabilities of regions (Penrose, 1959; Boschma and Frenken, 2012).

Against this backdrop, the primary aim of this paper is to analyse the evolution of knowledge complexity in Irish NUTS3 regions over the period 1981 – 2010. More so for Ireland than any other developed economy is its topical relationship with Foreign Direct Investment (*FDI*). Here, the principle question has always been, do local or foreign firms contribute more to the technological development of regional economies? Following Balland and Rigby (2017)[1] we build a 2-mode structural network to develop a knowledge complexity index (*KCI*) for Irish regions. The KCI is based on more than 3,500 patent records from the European Patent Office (*EPO*), and combines information on the technological structure of eight NUTS3 regions and the 35 aggregate technologies in which they have a Relative Technological Advantage (*RTA*). The KCI quantifies the complexity of the knowledge produced by each region, and thereafter extrapolates whether it is 'sticky' (non-ubiquitous) enough to only be produced in a few key regions, or if it is spatially footloose.

Our results indicate that the most complex technologies tend to be produced in a few diverse regions. For Ireland, these technologies are almost exclusively produced in Dublin, and or, the South-West and the Midlands region. Secondly, the majority of this complex knowledge is generated in technology classes where the share of foreign activity is greater than local firms. Lastly, we generate an entry model to compute the process of complex regional diversification. Complex regional diversification is fundamentally different to related diversification insofar as it examines how a region develops a comparative advantage in a technological domain more complex than those already present in that region. As such, we focus our attention only on those technologies with the highest KCI values, as these technologies are said to underpin the European Union's Smart Specialisation thesis (Foray *et al.,* 2009; 2011; McCann and Ortega-Argilés, 2013; 2015).

The remainder of this paper is organised as follows. Section 2 provides an overview of the key literatures of technological relatedness and knowledge complexity. Section 3 describes the use of patent data as well as the fundamental principles of knowledge

[1] The contribution of Balland and Rigby builds off the earlier work of Hidalgo and Hausmann(2009) who developed a Knowledge Complexity Index for countries.

complexity. Developing on this, Sections 4 and 5 operationalise the knowledge complexity index and address the papers main research questions. Section 6 is the model itself while Section 7 concludes and highlights some future research direction.

2) LITERATURE REVIEW

Two phenomenon characterise modern society. Firstly, that the production of economically valuable knowledge is central to economic prosperity and long term regional development (Schumpeter, 1939; Nelson and Winter, 1982; Lundvall, 1992; Metclafe, 1994; Hodgson, 2004). Secondly, that this type of knowledge is geographically bound (Jaffe *et al.,* 1993; Almeida and Kogut, 1997; Zucker *et al.,* 1998; Breschi and Lissoni, 2009; Thompson *et al.,* 2005; Sonn and Storper, 2008). Taken together, these two characterises – and extensions thereof - have cultivated in what is now commonly known as the "evolutionary turn" in economic geography (Grabher, 2009). At the core of this evolutionary approach, is an appreciation of the role of history in explaining how, experiences and competencies acquired over time determine present configurations as well as future regional trajectories (Kogler, 2015). Evolutionary theorists have long considered the importance of history in explaining regional development, as it provides a framework for understanding the uneven spatial distribution of socio-economic realities as a path dependent phenomena characterized by the recombination of related (Dosi and Nelson, 2010) and unrelated activities (Castaldi *et al.,* 2015).

This view of regional development through related diversification is not exclusive to economic geography. The seminal contribution of Hidalgo and Hausmann (2009) and more recently Hausmann *et al.,* (2011) and Hidalgo (2015) retain these geographical arguments, while simultaneously introducing a complex dimension to the study of regional diversification. Here complexity is defined iteratively, using information on the diversity of countries that make a product and the ubiquity of other products that that country produces (for a more in depth discussion see Hidalgo, 2015). Combing insights from complex systems (Simon, 1962) and network complexity (Barabási, 2011), the principle argument is that disparities in economic growth can be explained by the ubiquity (complexity) of capabilities present in a countries, as more complex products reside in a fewer countries. Extending these arguments to a regional level, the uneven spatial distribution of socio-economic activities and the lumpiness of knowledge production (Rigby, 2015) is therefore not simply a by-product of the economic diversity of that region, but more importantly by the complexity of the knowledge and know-how embedded in its networks. In their pan European study, Antonellia *et al.,* (2016) find evidence to this effect demonstrating that it is not just related knowledge that matters for the generation of new knowledge, but above all else, the relative scarcity of specific subsets of knowledge present in individual regions. Balland and Rigby (2017) draw similar conclusions while mapping the geography of complex knowledge in the US. They find that regional differences can be explained not just in terms of technological diversify, but more importantly by the amount of complex (tacit) knowledge embedded in that region.

In addition, they also find that not all knowledge is equal and provide new insights into the increasing importance of geographical proximity in the globalised economy. Indeed, while less complex knowledge might be considered footless. Complex knowledge, which ultimately underpins long terms competitive advantage retains a strong geographical dimension resulting in its production being carried in a select few regions (Markusen, 1996; Gertler, 2003; Boschma, 2017).

The popularity of this geographic dimension is echoed in the successes of a number of key industries; ICT in Silicon Valley (Saxenian, 1994), fuel cell technology in the Baden-Wuerttemberg region (Tanner, 2014), speciality wine in Piedmont (Morrison and Rabellotti, 2009) or the media cluster in Leipzig (Bathelt, 2005). For economic geographers, it is not what divides these industries that makes them interesting, but what connects them. Despite differences in their economic ecology what these industries all have in common are a series of localised learning procedures which makes imitation or replication elsewhere difficult if not impossible. Moreover, what gives these regions their prowess is a unique set of capabilities embodied in their economic, social and organisational networks (Hidalgo and Hausmann, 2009). Hausmann and colleagues refer to these capabilities as “modularized chunks of embedded knowledge” (Hausmann *et al.,* 2011, p. 17), colloquially known as the person-byte, but it can also include other institutional, cultural and social amenities (O’Cleary, 2016).

A useful analogy for conceptualising the embeddedness of an region (and by extension its complexity), is trying to move a jig-saw puzzle containing many pieces from one table to another. Its intricate makeup results in the pieces of the jig-saw beginning to fall as you try and move it. This implies that the difficulty in moving a jig-saw puzzle – like an industry – increases with the number of components (Hidalgo, 2015). A more optimal solution would be to move the jig-saw in smaller pieces to a table that already possess pieces of the same jig-saw. Extending this analogy to our region-technology matrix, sees that industries are more likely to develop in regions that are technological related to their current knowledge base, *i.e.* where they can recombine existing technological structures to meet future demands.

That regions diversify into industries that are technological proximate to their current specialisation should come as no great surprise (see; Content and Frenken, 2016 for an overview). Inspired by the earlier work of Hidalgo *et al*., (2007) a series of follow up studies have confirmed that regions/firms/technologies diversify into activities that are proximate to their current specialisation (Neffke *et al.,* 2011; Boschma *et al*., 2015; Rigby, 2015). Using information of the co-occurrence of technology classes listed on patent documents, the knowledge space is an intuitive way to model the processes of technological specialisation/diversification of a regional economy. Prior research for the US knowledge space has linked relatedness between technologies to faster rates of patenting per worker (Kogler *et al.* 2013), while Rigby (2015) found that technologies that where related to the regions an existing knowledge base had a high probability to enter that region that those technologies that did not. In a not too dissimilar vein, Boschma *et al.,* (2013) have also demonstrated that the probability of a US metropolitan area gains a new technology class increased by 30% if the level of relatedness with existing technologies in the city increases by 10%, while the exit probability of an existing technology decreases by 8%. Similar results were also found by Tanner (2014, 2016) for the growth of fuel cell technologies throughout Europe, for nanotechnologies in European regions (Colombelli *et al.* 2014) and for the spatial diffusion of the rDNA technology across US metropolitan regions (Feldman *et al.* 2015).

The thread that connects the literatures of economic complexity and technological relatedness is the intuition that certain types of knowledge are more or less mobile than others, and that this mobility is in part reflected by the complexity of that technology. Early attempts by Fleming (2001) and Fleming and Sorenson (2001) to measure the complexity of technologies suggest a landscape of recombinant search, akin to the fitness landscape models proposed by Kauffman (1993)[2]. Their proxy for complexity is the difficulty that arises when

[2]The idea behind the fitness landscape was originally developed by the biologist Sewall Wright in 1932 and was used to visualize the relationship between genotypes and reproductive success. Since then, it has been adapted by complexity and evolutionary theorists as a means to understand complex evolutionary patterns.

trying to recombine different technology classes listed on patent documents. In more recent applications, Hidalgo and Hausmann (2009) develop a measure of complexity based on the diversity of countries that make a product, and the ubiquity of other products that that country produces. Moving down the geographical scale, Balland and Rigby (2017) develop an eigenvector approach of the original methodology and map the geography of complex knowledge throughout the US. The current investigation utilises the methodology outlined in Balland and Rigby (2017), while introducing an additional element, namely; whether more complex knowledge is created by local or foreign firms. Not least since Bathelt *et al.,* (2004) has the importance of non-local networks been recognised throughout economic geography.

Along these lines, Neffke and colleagues have challenged seemingly superior nature of local versus non-local knowledge flows for enacting structural change. In the authors' own words, they argue beyond local interactions, demonstrating that "radical structural change predominantly depends on non-local firms and entrepreneurs transferring new activities to the region" (Neffke *et al.,* 2014, p. 4). Findings such as these are becoming increasingly common throughout economic geography with a growing body of literature now explicitly focusing on the role of non-local actors and their ability to introduce external types of knowledge (Owen-Smith and Powell, 2004; Giuliani, 2011; Breschi and Lenzi, 2015; Zhu *et al.,* 2015). In spite of this, no such investigation has yet to consider the role played by foreign firms in generating more or less complex knowledge. This study endeavours to address this gap.

Finally, getting accurate information on technological knowledge is not easy, but it is possible. The difficulty is that knowledge is an intangible good. You cannot hold knowledge the same way you can hold an apple or cycle a bike. This scepticism is aptly summarised by Paul Krugman (1991, p. 53), when stating that "knowledge flows are invisible; they leave no paper trail to which they may be measured or tracked". In defiance of this, Jaffe *et al.,* (1993, p. 578) demonstrate that "knowledge flows do sometimes leave a paper trail", in the form of patent citations, and in doing so demonstrate a way to trace the production of knowledge over space and through time (Almeida and Kogut, 1997; Sonn and Storper, 2008). While the current investigation does not use patent citation analysis, it does employ patent statistics to analysis the evolution of complex knowledge. More specifically it takes advantage of the individual technology classes listed on patent documents and derives a measure of complexity based off the ubiquity of these classes and the diversity of regions that produce them (Balland and Rigby, 2017). Finally, that patents are an imperfect and limited measure of economic and innovative activity are well known (Pavitt, 1984; Griliches,1990). Nevertheless, it is generally well accepted that patents - as a proxy of innovation - provide a good indication of the processes of knowledge creation and diffusion, especially on a regional level (Acs *et al.,* 2002). They also provide key insights into the organisational activities of those actively involved in the production of new knowledge (Usai, 2011).

3) Knowledge Complexity Network

Networks have always played a formative role in economic geography (Glückler, 2007). In the past, the study of network dynamics has provided key insights into the transfer of knowledge between firms (Inkpen and Tsang, 2005), for social networks (Breschi and Lissoni, 2009) and for scientific collaborations between European regions (Hoekman *et al.*, 2010). At the same time, the recent geographical turn has cultivated a more spatial perspective directed at understanding the formation and evolution of these ties (Boschma and Frenken, 2012). Influential in this line of enquiry was the contribution of Bathelt *et al.*, (2004) who questioned whether local or non-local networks matter most for economic growth? Consequently, it has been argued that what matters most for regional development are approaches the strategize a more open ended and collaborative approach to innovation, as no single firm/industry has the capacity to generate all the knowledge they require internally (Neffke *et al*., 2014). Examining the role of knowledge gatekeepers for the expansion of U.S. cities, Breschi and Lenzi (2015, p. 783), demonstrate that,

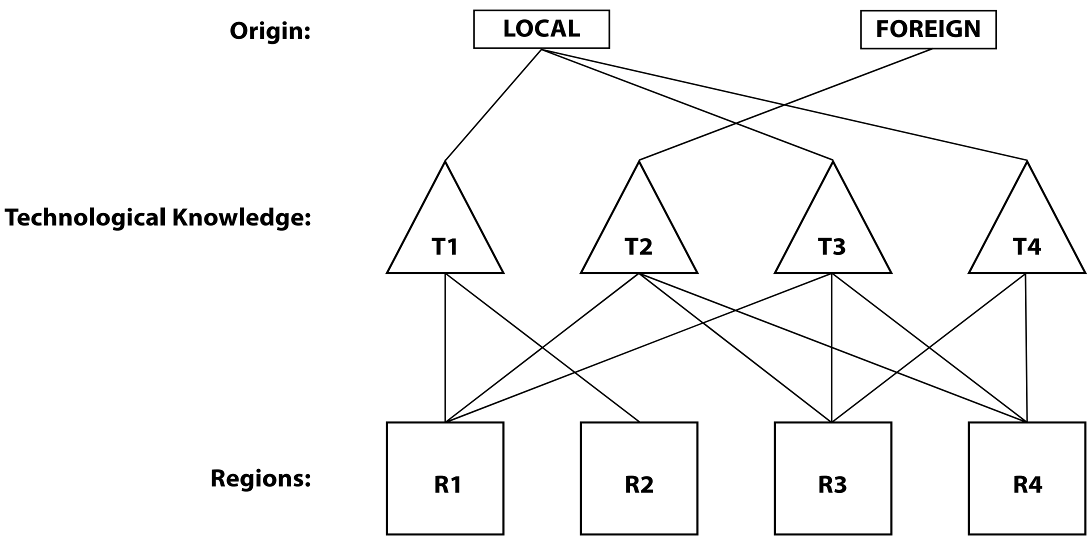
> *Dense interactions at the local level (i.e. local buzz) combined with embeddedness in global networks (i.e. global pipelines) allow one to exploit the advantages deriving from trusted and repeated ties at the local level with non-redundant information deriving from external sources.*

Armed with such a logic, the primary aim of this paper questions whether the more valuable (complex) knowledge is generated by local or foreign firms? To do this, requires a network that links technologies and regions. This requirement lends itself to the formation of a modified bipartite graph (Borgatti 2009; Balland and Rigby, 2017); which in addition to connecting technologies and regions, also links these technologies to their country of origin (Figure 1)[3].

To construct the knowledge complexity network, we make use of patent data from the European Patent Office (*EPO*) for the years 1981 – 2010, and information on the country of origin, provided by Bureau van Dijk's *FAME* database. The use of patent statistics has a long tradition within economic geography, with their popularity being directly relating to the wealth of information contained within individual patent documents (Rigby, 2000). Furthermore, since our investigation is primarily concerned with the formation of new knowledge, as well as the organisational processes that results in this production, patent data has been listed as an excellent source of information (Usai, 2011). More technically, we make use of two distinct pieces of information, the 629 primary technology classes (T nodes in Figure 1) and their corresponding NUTS3 region (R nodes in Figure 1).

Next to ascertain which type of firm - local or foreign - is generating the more complex knowledge we need reliable information on that firm. To do this we make use of the *FAME* database provided by Bureau van Dijk. Among other things, this database contains information on the ownership, finance and governance of Irish firms. This enables us to

Figure 1, Region - Technology Network



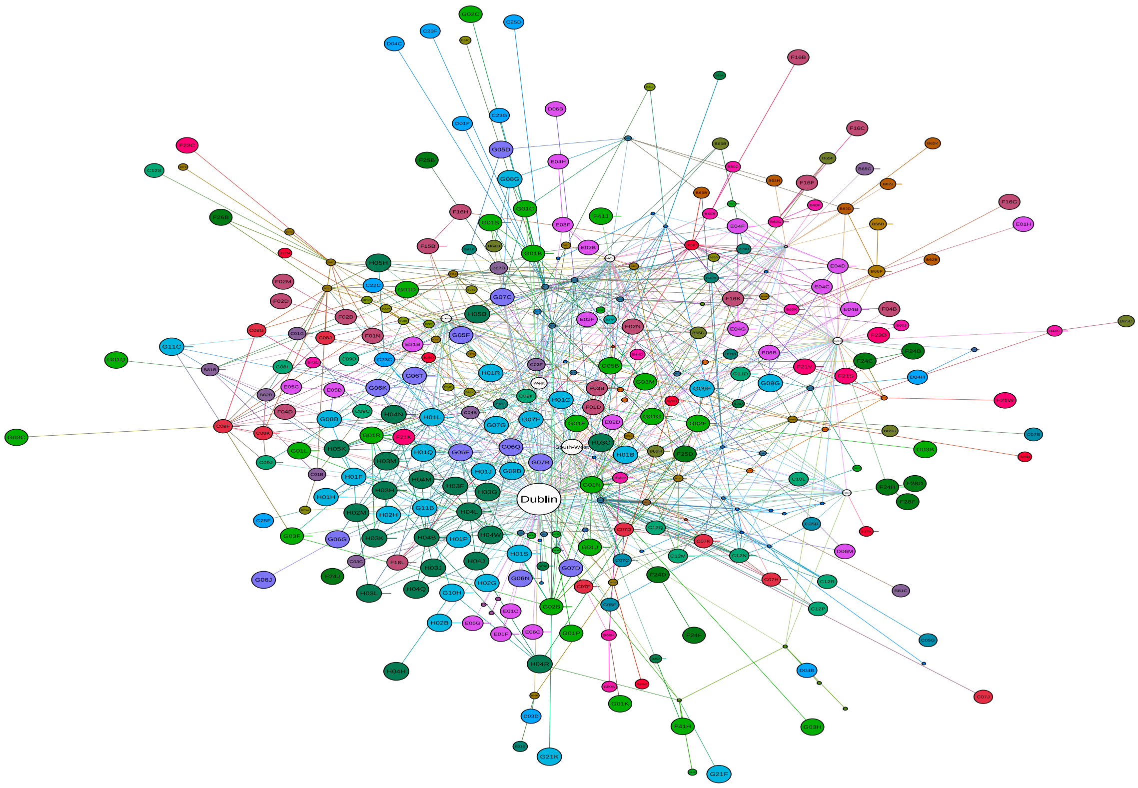
[3] A detailed and thorough explanation of distinguishing between local or non-local will be explained in the following sections.

define whether a firm is an Irish firm, or a foreign firm operating in Ireland. For example, IBM is an American firm, but it has an Irish branch. So too does Dell, Intel, Apple, Hewlett-Packard, Logitech, Microsoft and Amazon to name but a few. Current approaches in the literature would list an IBM technology (patent) as Irish if the address of the primary inventory is in Ireland, even though the firm itself is American. This is a major problem considering the incentives that are offered to foreign firms to operate in Ireland, as it would make it appear as if local firms are generating the complex knowledge, even though the firm itself is foreign. We include only those firms registered in Ireland between the years 1981 – 2010, and use country ISO codes to delineate between local and foreign firms. To clarify this point, we categorise a firm as Irish if their corresponding ISO code is "IE" and foreign otherwise.

The knowledge complexity network is operationalised as an *a* by *b* two mode matrices, where *a* = 8 NUTS3 regions and *b* = 629 technology classes. Figure 2. provides a visual representation of the knowledge space for Ireland for the years 2001 – 2010. Throughout this paper, we fixate our attention primarily on these years (unless otherwise stated), as these years represent a period of unprecedented structural change commonly associated with the Celtic Tiger[4]. The individual nodes in Figure 2. have two purposes, the eight white nodes represent Irish NUTS3 regions, while the coloured nodes represented the individual technology classes. Following Schmook (2008), the network has been aggregated into the 35 main technology classes. Here, it is assumed that nodes that appear in the same broad technology class share a similar knowledge base, or that the competencies used in the production of one technology class can be easily reconfigured to develop another. Within the network, the positioning of the regions (white nodes) are fixed while the relative positioning of the technology classes around them, reveals those technology classes in which regions have an RTA. The size of the white nodes reflects the technological capabilities of that region, and in doing so highlights a core – periphery structure within the network. The centre of the network is dominated by Ireland's capital city Dublin, a diverse region active in

[4] The Celtic Tiger represents a period of economic development in Ireland during which time GDP increased at an average rate of 9.6% per annum (Internationally Monetary Fund, 2001) and active industrial employment increased by 1.4% per annum (Cambridge Econometrics, 2015).

Figure 2, Irish Knowledge Space, 2001 - 2010



several technologies. This basket of technologies primes Dublin as an ideal location for technological recombination as existing technologies can easily be reconfigured to create new technologies. In direct contrast to Dublin are the South-East and Border regions who populate more periphery areas of the knowledge space. Finally, there was those regions whose economic structure is characterised by a specialisation in specific technologies, namely; the West's reliance on medical devices and the South West in pharmaceutical technologies[5].

Despite advances in visualisation techniques, network algorithms and databases, networks will only ever be able to provide preliminary insights into the development of regions and the evolution of technologies (Balland and Rigby, 2017). A richer discussion requires a more systematic framework, one that combines information on both the geography and complexity of technology classes. It is to these questions that this paper now turns.

[5] See figure 3 below for a more detailed breakdown of the technological composition of Irish NUTS 3 regions.

4) MEASURING KNOWLEDGE COMPLEXITY

So how would one go about measuring complexity? According to, Nicolas and Prigogine (1989, p. 36) the immediate problem associated with complexity is a theoretical one, insofar as, "complexity is one of those ideas whose definition is an integral part of the problems that it raises". The second problem, at least in economic geography is more empirical, reflecting a lack of suitable data sources for such investigations. Fortunately, many of these concerns have recently been addressed as previously underutilised information in several databases are now readably been exploited (Hidalgo *et al.,* 2007; Neffke *et al.,* 2011; Kogler *et al.,* 2013).

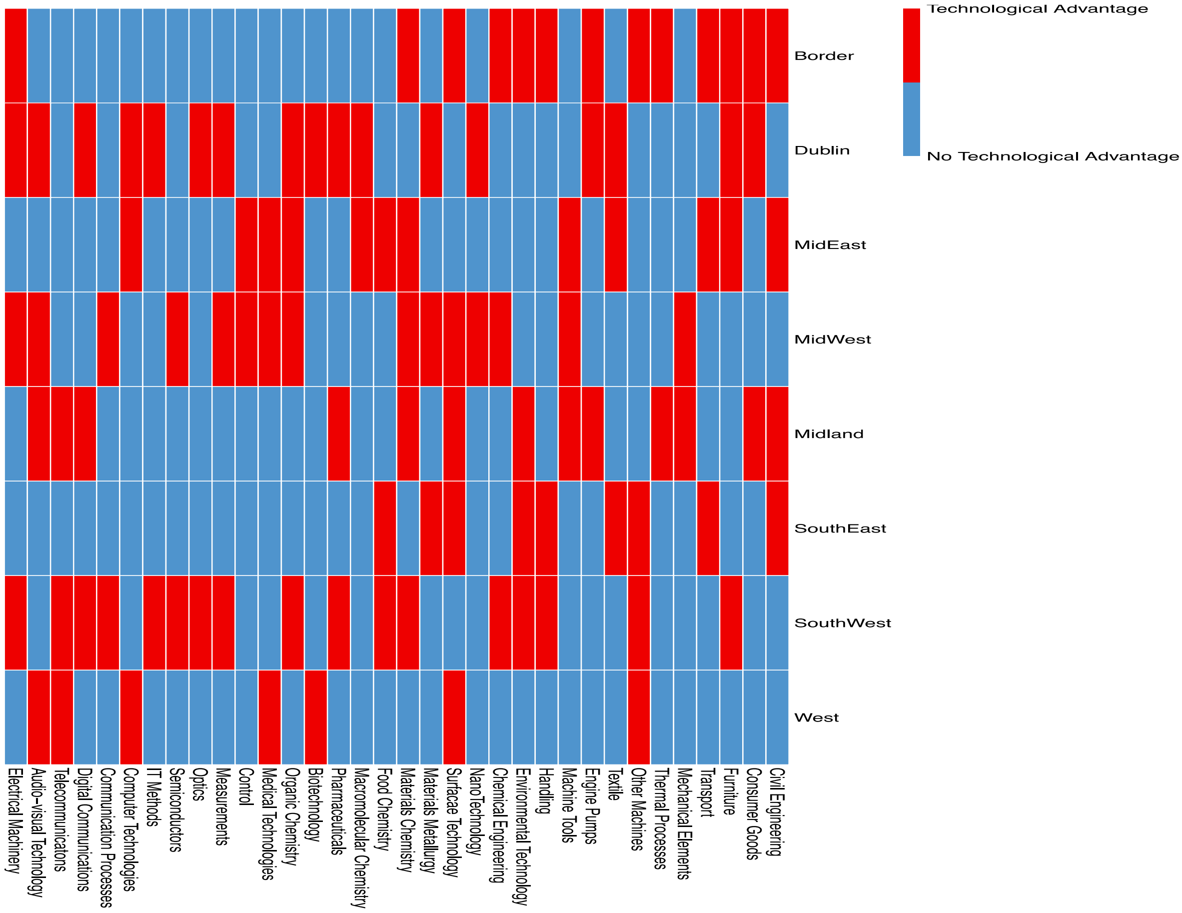
Developing on the *region-technology* matrix outlined above, Figure 3. provides a more direct interpretation of the technological composition of Irish NUT3 regions. As has become commonplace, we only focus on those regions r that have a technological advantage in a given technology i. Put differently, $RTA_{r,t}(i) = 1$ if:

$$\frac{patents_{r,i}^{t}/\Sigma_i patents_{r,i}^{r}}{\Sigma_r patents_{r,i}^{t}/\Sigma_r \Sigma_i patents_{r,i}^{t}} \geq 1 \qquad (1)$$

Nevertheless, the sheer presence of absence of an RTA does not comment on the complexity of this knowledge, or whether that knowledge was generated by local or foreign firm. In pursuit of these goals, requires a methodology that simultaneously combines information the diversity of regions and the ubiquity of technologies produced.

A fertile starting point for these discussions is the *method of reflections* methodology developed by Hidalgo and Hausmann (2009). This is a novel approach which infers the complexity of capabilities underlying an economy by combining information on countries and products. In a similar fashion, Balland and Rigby (2017) use USPTO patent data to map the complexity of technologies produced within MSAs. Following Caldarelli *et al.*, (2013) these authors developed an alternative measure of complexity using an eigenvector reformulation of the original methodology. More specifically, their measure of complexity is computed as the second largest eigenvector of the region-technology matrix and combines information on the diversity of regions (*i.e.* number of patents produced by a region) (see Albeaik *et al.,* 2017, for a more technical summary).

Figure 3, Regional Technological Advantage, 2001 - 2010



$$DIVERSITY = K_{r,0} = \sum_{i} M_{r,i} \qquad (2)$$

and 2) the ubiquity of their technologies (*i.e.* the number of regions with an RTA in the technology).

$$UBIQUITY = K_{i,0} = \sum_{r} M_{r,i} \qquad (3)$$

Using this information, the current investigation advances this line of enquiry while introducing two additional elements. Firstly, seen as this paper is chiefly concerning with whether more complex knowledge is generated by local or foreign firms, we have endeavoured to delineate between the two in manners previously discussed. Secondly, whereas the contribution of Balland and Rigby (2017) primarily focused on unravelling the geography of complex knowledge, in terms of which cities produced the most complex knowledge. Our paper focuses on the evolution of this knowledge. Such distinctions lead to the formation of the following two equations:

$$KCI_{region} = K_{r,n} = \frac{1}{K_{r,0}} \sum_{i} M_{r,i} K_{i,n-1} \tag{4}$$

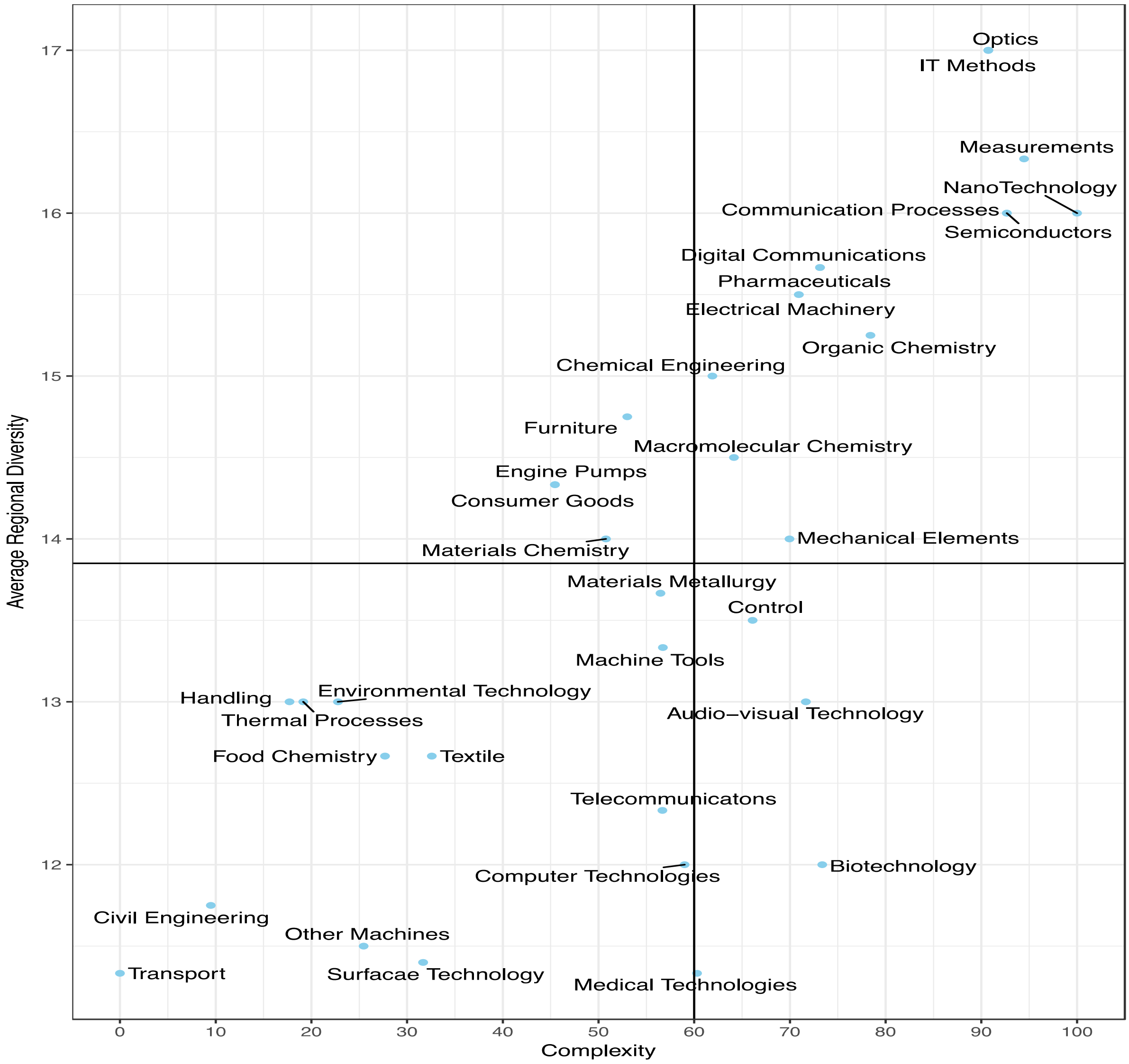
$$KCI_{technology} = K_{i,n} = \frac{1}{K_{i,0}} \sum_{i} M_{r,i} K_{r,n-1} \tag{5}$$

By combining information on the diversity regions and the ubiquity of technologies, the *method of reflections* methodology calculates jointly and iteratively the average of the proceeding measures. Or to put it more simply, each additional iteration n in equation (4) and equation (5) makes use of the others calculation for the previous step. Since this paper primarily focuses on the complexity of technologies, additional iterations $n = 2 \ldots 3 \ldots 20$ in equation (5) provides a more detailed measure of the complexity of a given technology by using information of the diversity of regions that have a technological advantage in that technology.

5) TECHNOLOGICAL COMPLEXITY IN THE IRISH KNOWLEDGE SPACE

Developing on the methodology outlined above, the remainder of this paper shifts its attention towards answering the primary research question, namely; *whether more valuable (complex) knowledge is generated by local or non-local firms?* Theory argues that the relationship between complex technologies and complex regions are essentially two sides of the same coin. This symbiotic relationship boils down to the fact the advanced regions produce complex technologies and that complex technologies are produced by more advanced regions. Figure 4. plots the relationship between the complexity of individual technologies and the diversity of regions that produce them. The strong and positive relationship between the two variables (0.81) indicates that more complex (non-ubiquitous) technologies are produced in more diversified regions, while ubiquitous technologies can be easily produced by many regions. Intuitively this makes sense, as diverse regions have at their disposal a wide range of ‘capabilities’ from which they can produce more complex structures, whereas technologically specialised regions would struggle to meet these

Figure 4, Regional Diversity and Complexity of Aggregate Technology Classes, 2001 – 2010



demands[6] Hausmann *et al.,* (2011).

Using information on the mean complexity (vertical line) and mean diversity (horizontal line) it is possible to dissect the graph into four quadrants. In the bottom left quadrant are the less complex (ubiquitous) technologies that are produced in more specialised regions (Textiles, Transport and Other Machines). Similarly, the bottom right quadrant is equally as specialised but the type of technologies produced in these regions are a lot more sophisticated, meaning that imitation is highly unlikely due to their complex structure (Medical Technologies and Biotechnology). Moving up the y-axis reveals a more diversified

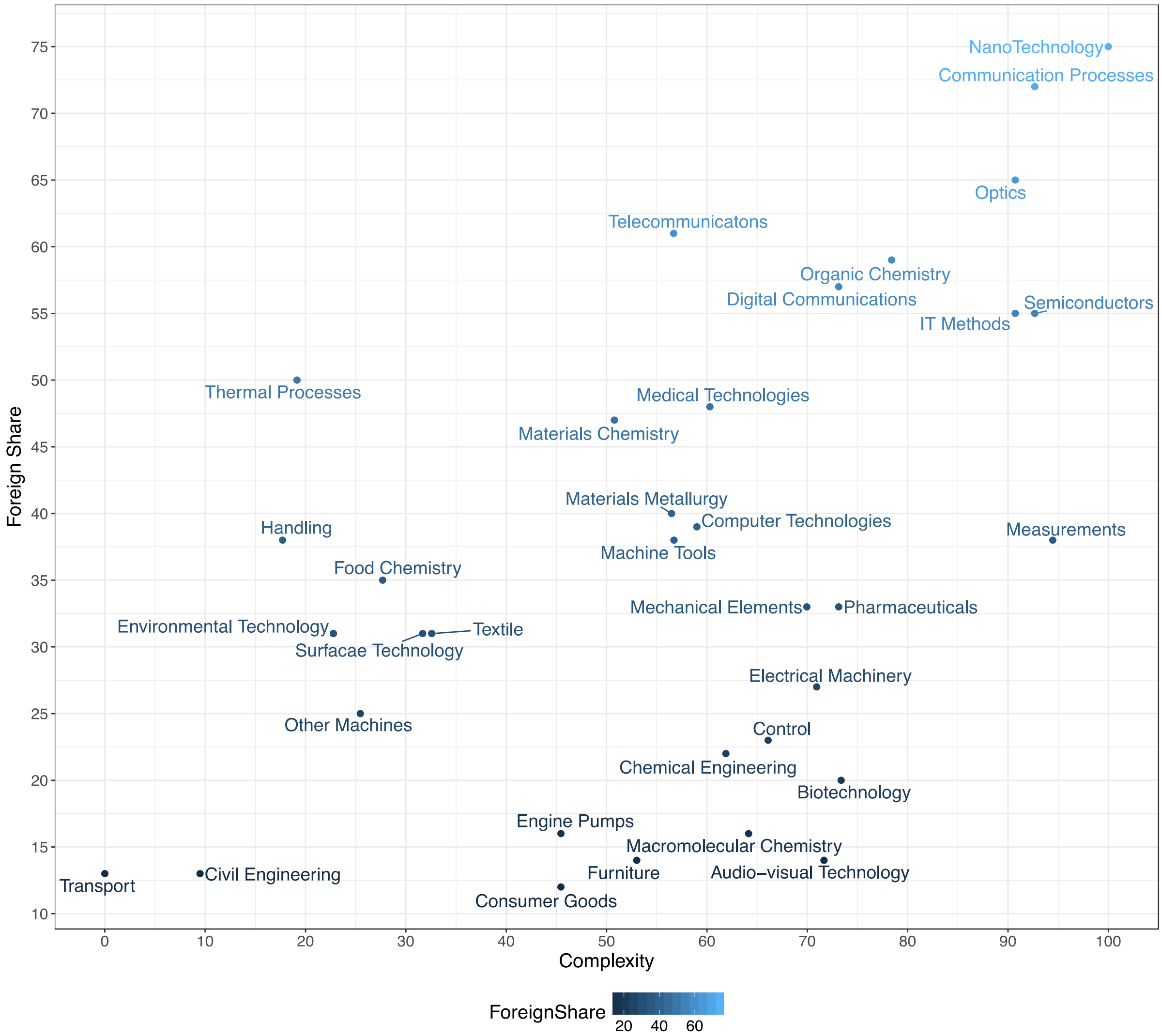
[6] There are of course exceptions to this rule, but generally speaking the most complex technologies are produced in regions with a highly diverse knowledge base.

economic structure. The top right quadrant houses the most complex (non-ubiquitous) technologies that are produced in more diversified regions (Optics, Nanotechnology and Measurments). The case of Nanotechnology demonstrates the interaction between complexity and diversify particularly well as a technology class that is intrinsically interdisciplinary (Leydesdorff and Schank, 2008). Moreover, given its early lifecycle, Bonaccorsi and Thoma (2007) have highlighted that nanotechnology requires a more diverse instrument set compared to more mature technologies.

But what about the firms generating the more complex knowledge? While Figure 4. details the complexity of the main technology classes, it does not describe which firms are generating the more complex knowledge. To address these concerns, Figure 5. plots the relationship between the share of foreign activity for a specific technology against the complexity of that technology. To further clarify this point, *Transport* has a low overall share of foreign activity (13%) and a high share of local activity (87%), *i.e.* foreign firms are not as engaged in this technology class as their local counterparts. Moving up the y-axis this trend gradually changes as the share of foreign firms' activity increases. This trend peaks at 75%, where for Nanotechnology where foreign activity is three times higher than local firms. Indeed, it is particularly interesting to note that the majority of complex technologies (KCI < 80) are generated in classes where foreign firms are most active. Among others, these technologies have been identified both nationally (Department of Jobs, Enterprise and Innovation, 2015, 2016) and internationally (OECD, 2015) as the key enabling technologies of the future and, as those technologies that underpin the smart specialisation thesis (Foray *et al.*, 2011; Heimeriks and Balland, 2016).

This is not to argue that only foreign firms are generating complex technologies. Measurements consistently ranks as one of the most sophisticated technologies in the Irish knowledge space (KCI > 90), and its share of foreign activity is less than 40%. Similarly, the share for Biotechnology and Pharmaceuticals are equally low, while their KCI is greater than 75. Lastly, and just as important, Figure 5. also reveals a cluster of moderately complex technologies (KCI <50) with a comparatively equal share of engagement, namely; Medical Technologies, Macromolecular Chemistry and Materials Chemistry.

Figure 5, Technological Complexity Relative to Foreign Share.



Developing on these ideas, Table 1 provides further information on complexity of the top ten aggregate technology classes for the period 2001 – 2010. It also provides a description of each technology class, ubiquity of that technology, regional indicators and the share of foreign activity. In Table 1, seven of the ten technologies are associated with a higher foreign share. Alongside their complexity, these technologies have among the lowest ubiquity values (the number of regions that have RTA in each class), with the average ubiquity score of the entire Irish knowledge space been 3.7.

Although beyond the scope of this paper, there are a series of important geographical implications to these arguments. In their pioneering paper, Hidalgo and Hausmann (2009) link product complexity at a country levels to higher levels of Gross Domestic Product (*GDP*), indicating that those regions that export more complex products tend also to be more

Table 1, Top 10 Aggregate Technology Classes, 2001 - 2010

TECHNOLOGY	DESCRIPTION	KCI	UBIQUITY	FOREIGN SHARE	REGION(S)
Nanotechnology	*Microstructural Technology*. This field covers micro-structural devices or systems, including at least one essential element or formation characterised by its very small size. It includes nanostructures having specialised features directly related to their size.	100	2	75%	Dublin Midlands
Measurements	*Physics*. This class covers, in addition to "true" measuring instruments, other indicating or recording devices of analogous construction, and also signalling or control devices insofar as they are concerned with measurement and are not specially adapted to the particular purpose of signalling or control.	94	2	38%	Dublin Mid-West
Communication Processes	*Electricity*. This field covers basic technologies such oscillation, modulation, resonant circuits, impulse technique, coding/decoding. These techniques are used in telecommunications, computer technology, measurement and control.	92	2	72%	Midlands South-West
Semiconductors	*Electricity*. This field comprises of semiconductors including methods of their productions. Integrated circuit or photovoltaic elements also belong to this field.	91	2	55%	Mid-West South-West
Optics	*Physics*. This field covers all parts of traditional optical elements and apparatus, but also laser beam sources. In recent years new optical technologies such as optical switching have become more relevant.	90	2	65%	Dublin South-West
IT Methods	*Physics*. Data processing systems or methods, specially adapted for the administrative, commercial, financial, managerial, supervisory or forecasting purposes.	90	2	55%	Dublin South-West
Organic Chemistry	*Chemistry*. pure chemistry, which covers inorganic compounds, organic compounds, macromolecular compounds, and their methods of preparation.	78	2	59%	Dublin South-West
Biotechnology	*Chemistry*. Biotechnology is defined as a separate field, although it is linked to a variety of different applications. Like organic chemistry or computer technology, it is a crosscutting or generic technology.	73	2	20%	Dublin West
Digital Communications	*Electricity*. This field was part of telecommunications. At present, it is a self-contained technology at the border between telecommunications and computer technology. A core application of this technology is the internet.	73	2	57%	Dublin South-West
Pharmaceuticals	*Human Necessities*. Preparation for medical, dental or toilet purposes. Specific therapeutic activity of chemical compounds or medicinal preparations.	73	2	33%	Dublin Midlands

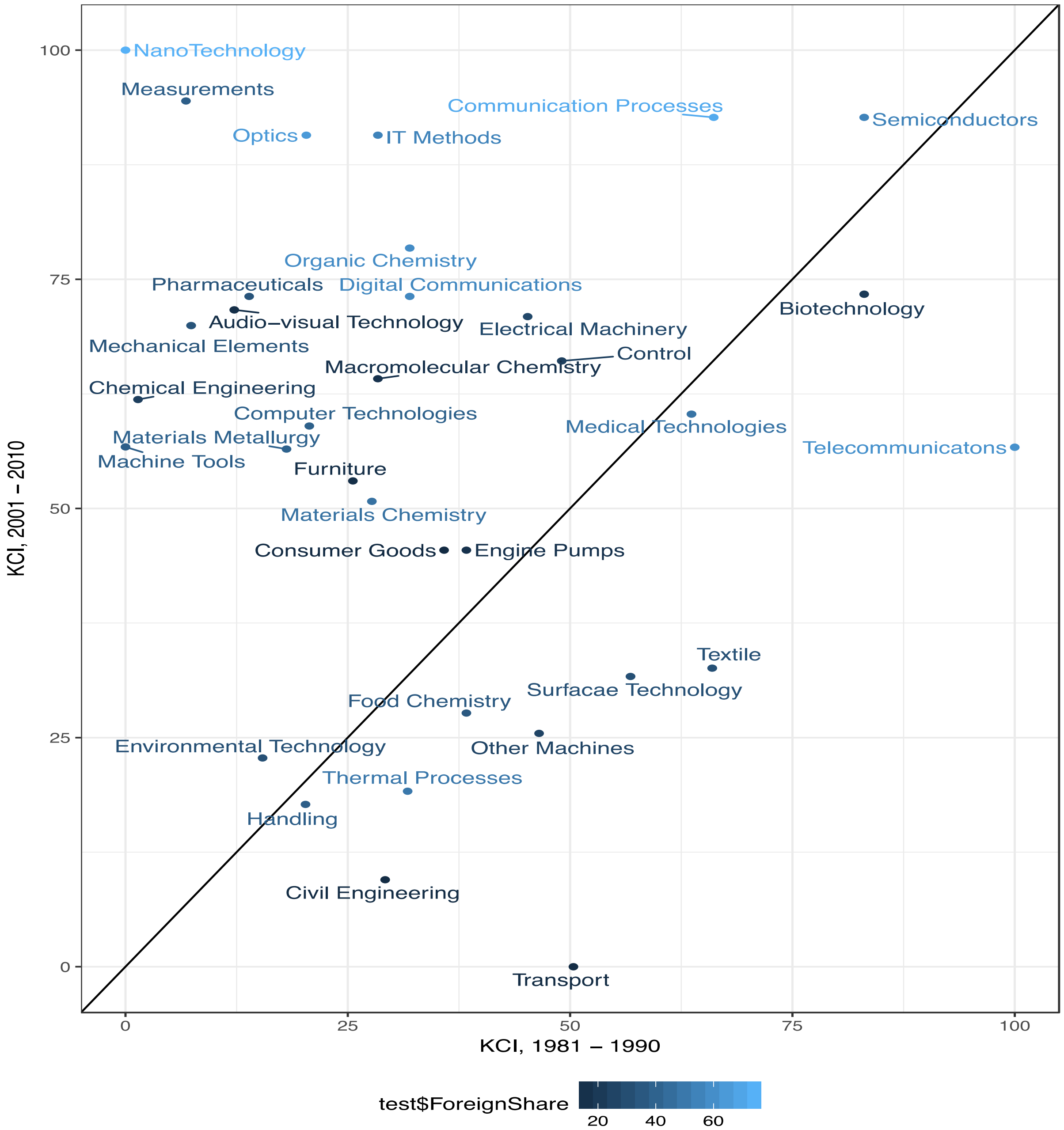
prosperous. Extending these arguments to a regional scale, Balland and Rigby (2017), find wide geographic variations in knowledge complexity of US MSAs with relatively few regions being able to produce the most complex technologies. To this effect, the final column in Table 1 provides information on the NUTS3 regions in which these technologies reside. The vast majority of these technologies are present in Dublin and either in the South-West or Midlands. These regions where specifically targeted to spearhead Ireland's three cluster approach throughout the 1980s so it is not surprising that these technologies are found there (Culliton, 1992; Clancy *et al.,* 2001).

For evolutionary theorist Schumpeter (1939) the relentless endeavours of the firm to generate new technological knowledge rests solely on the process of 'creative destruction'. This process describes how the evolution of the space economy is driven by a series of micro-geographic/economic interactions that "forever alters and displaces the equilibrium state previously existing" (Schumpeter, 1943, p. 64). Indeed, deciphering the ebb and flow processes of technological change, has become a cornerstone throughout evolutionary economic geography with a series of recent contributions focusing explicitly on how technologies enter and exit regions (see, Kogler *et al.*, 2016; Rigby 2015; Boschma *et al.*, 2015). Thus, it is logical to reason that the complexity of these technologies will change as new technological structures rise to prominence and as old ones' decline. Figure 6. graphs how the complexity of technological knowledge has changed from the period 1981 - 1990 to 2001 – 2010[7]. As with before, these technologies have been catalogued to reflect foreign share.

Technologies located above the forty-five-degree line have greatly improved their complexity, while those below the forty-five-degree line have experienced a decline in their relative complexity. Unsurprisingly, the technologies that have exhibited the greatest increase in their KCI are those identified as the 'smart technologies' of the future *e.g.* nanotechnology, measurements, optics, and IT methods (Forey *et al.*, 2011). At the same time, more traditional technologies - Transport, Other Machines and Textiles - have exhibited a decline as these technologies have become easily reproducible by many regions. As with before, it should be noted that for Ireland the technologies with the greatest increase in KCI values are

[7] These values have been normalised to allow comparison between time periods.

Figure 6, Change in Technological Complexity, 1981 - 2010



those more commonly associated with foreign firms (excluding Measurements), which serves as an indicator to which type of firms are generating the more complex knowledge.

From the previous discussions, we know that those regions capable of producing complex technologies enjoy a position of economic stature, and given the profit motif that necessitates innovation, this usually arises in their ability to extract quasi-monopolistic rents (Schumpter, 1939). It is therefore reasonable to assume that, given the opportunity regions would prefer to specialise in more complex technologies as opposed to more standardised ones. Translating this intuition into a regional policy directive would see policy makers favour policies of complex regional diversification over related diversification as this implies diversifying into a technological domain more complex than those already produced (Balland *et al.*, 2017).

6) Complex Regional Diversification

At its core, complex diversification is the processes through which regions diversify into technological structures more complex than those already present in the region. In the final section of this paper, we present our main empirical results. Our panel is made up of Irelands 8 NUTS3 regions and the 10 most complex technologies as listed in Table 1 over the period 1981 – 2010. In this respect, we acknowledge that Ireland is a small country with a nuanced history, so as a robustness check our finding have been compared against the EU15 knowledge space[8]. More importantly, what follows should serve as an entry point for others to also begin investigating these processes of complex diversification. To these ends, our model occupies two interrelated purposes 1) in its predictive power and 2) in the mechanisms it identifies.

We have already detailed at length the benefits that accompany complex technologies, which should act as a strong justification as to why regions would want to specialise in them. The process of complex diversification is investigated using a panel version of a fixed effects entry model. The main variables of interest are *Relatedness Density,* which measures how related a complex technology is to the knowledge portfolio of a region (Balland, 2016b). *Technological Complexity* is the corresponding KCI for a given technology and *Technological Relatedness* which capture the total "technological distance" between technologies (Boschma *et al.,* 2015). Summary statistics of these variables are shown below.

Due to the small and restricted sample size (which may downplay the effects of *Technological Complexity*), we also include an interaction term between *Technological*

[8] Based on the authors own calculations these results are robust when compared against the EU15 Knowledge Space. Similar results were also found by Balland *et al.,* 2017 for the EU28 plus including Norway, Switzerland and Iceland.

TABLE 2, SUMMARY STATISTICS

VARIABLES	N	MEAN	SD	MIN	MAX
Entry	42	0.2625	0.441374	0	1
Relatedness Density	160	33.025	23.28169	0	100
Knowledge Complexity	160	61.2468	32.84711	0	100
Technological Relatedness	160	0.29409	0.104167	0	0.442
Complex_Relatedness	160	20.2405	13.03306	0	41.488
Knowledge Stock	160	238.6875	135.976	10	586
Active Employment	160	41.10875	21.6602	18.55	94.89

Complexity and *Technological Relatedness* to investigate whether complexity matters more, when these technologies are related. The intuition being that regions can 'jump further' *i.e.* into more complex technological structures if that jump builds on a set of localised capabilities. We also include a series of regional fixed effects $\emptyset_r$ and time fixed effects ∂_t as well as residual errors $\varepsilon_{i,r,t}$. Finally, standard errors are clustered at both the regional and technology level and all independent variables have been lagged by one time period to account for endogeneity. With these specifications in mind, leads to the formation of the following econometrics model:

$$
\begin{aligned}
&Complex\ Diversification_{r,i,t} \\
&\quad = \beta_1 RelatednessDensity_{r,i,t-1} + \beta_2 TechnologicalComplexity_{\,i,t-1} \\
&\quad + \beta_3 TechnologicalRelatedness_{\,i,t-1} \\
&\quad + \beta_4 TechnologicalComplexity * TechnologicalRelatedness_{i,t-1} + \emptyset_r + \partial_t \\
&\quad + \varepsilon_{i,r,t}
\end{aligned}
$$

As to be expected, Relatedness Density exhibits a positive and significant effect throughout each of our models. This finding is in line with both the literatures of regional diversification and economic complexity, seen as, regions are more like to diversify into a complex technology, if that technology is related to a pre-existing set of capabilities already present in the region. Next, the sign for *Technological Complexity* is consistently negative and varies in significance. This is consistent with the idea that complex technologies are a desirable diversification option for regions, but, given their complex structure are inherently

TABLE 3, COMPLEX DIVERSIFICATION MODEL

VARIABLES	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
Relatedness Density	0.0164***	0.0166***	0.0163***		0.0169***	0.0169***
	(0.00131)	(0.00130)	(0.00144)		(0.00147)	(0.00155)
Tech_Complexity		-0.00187*	-0.00211**		-0.00619**	-0.00619*
		(0.000811)	(0.000895)		(0.00172)	(0.00171)
Tech_Relatedness			0.269		-0.351	-0.353
			(0.433)		(0.399)	(0.406)
Complex_Relatedness					0.0176***	0.0177***
					(0.00654)	(0.00651)
Active Employment				-0.00541		0.00651
				(0.0105)		(0.00741)
Knowledge Stock				0.000179		0.000200
				(0.000173)		(0.000129)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160	160	160	160	160	160
Log Likelihood	1.955	4.238	4.723	-71.05	8.060	9.219

Note: The dependent variable is a binary taking a value of 1 if a region enters a complex technology and 0 otherwise. The models above focus exclusively on the ten most complex technologies, and this should be taken into consideration when interpreting. Standard errors are shown in the parentheses and have been clustered at the regional and technology level. Coefficients are statistically significant at the * $p<0.05$, ** $p<0.01$ and *** $p<0.001$.

more difficult to diversity into (it is also likely that these effects have been magnified given that the dependent variable only includes the ten most complex technologies, and the overall small sample size, N = 160). Similarly, the effects of *Technological Relatedness* fluctuates throughout each of the models. This would insinuate that it is not relatedness per se that matters for complex diversification, as there are a lot technologies that cannot be meaningful recombined to allow for more distant jumps in the knowledge space.

Model 5 and 6 include the full section of variables and the interaction term between *Technological Complexity* and *Technological Relatedness*. As previously discussed, these complex technologies have already been shown to be highly related to one another. In both models the interaction between complexity and relatedness is positive and significant revealing a region is more likely to diversify into a complex technological domain if that technology is related to an existing set of technologies currently present in the region. Finally, as a control, we include *Active Employment* which is a measure of active industrial employment based of Cambridge Econometrics (2015) and *Knowledge Stock* which is the number of patents in a region. The overall effects of both of these variables in our models are marginal.

Thus far in the literature it is fair to say that related diversification is the rule and seldom the exception (Neffke *et al.,* 2011; Boschma *et al.* 2015). Nevertheless, it is becoming apparent that other forms of diversification – unrelated and complex – can no longer be overlooked as they have the capacity to address numerous issues beyond the scope of a purely related approach, not least when considering knowledge re-combination, radical technological change, path creation and regional resilience (Martin and Sunley, 2006; Christopherson *et al.,* 2010; Tanner, 2014; Boschma and Capone, 2015; Castaldi *et al.,* 2015; Balland *et al.,* 2017). Moreover, although many authors have commented on the long term limitations of related diversification, far fewer have provided any recommendations (Boschma, 2016). In this regard, the results from Table 3 are an important first step in this direction. The inclusion of a complex dimension into regional diversification provides new insights in the branching and innovative capabilities of regions. At the same time, the application of these results has border implications throughout economic geography.

A prime example of this can be found alongside the European Union's Smart Specialisation thesis, which underpins long term growth and innovation policy throughout Europe. Smart specialization aims to enhance regional competitiveness by identifying and enabling those regions that have a particular 'strengths' in certain industries (technologies) (Foray *et al.,* 2011). Additionally, the thesis has also became embroiled with EU's funding allocation, principally in relation to H2020. The issue here is that there will always be more regions wanting to get funded, than funding available. So which regions (industries) should get funded? Current best practice favours the development of related industries, as these industries are better able to leverage their assets to meet future needs.

However, this should not be considered the only approach. In their recent contributions Balland and Rigby (2017) and Balland *et al.,* (2017) query what the addition of a complex dimension would mean for the smart specialisation thesis as a whole. They poise that, regional innovation policy support should not only target related diversification, but also complex diversification which would enable regions to branch out into technologies more complex than those already produced. In this context, complex diversification simultaneously and has high economic, social, industrial and technological value (Schoenmakers and Duysters, 2010). In the author's own words this would create bottom-up policy which enables regions to "leverage their existing capabilities to develop and secure comparative advantage in related high-value-added activities" (Balland *et al.,* 2017, p. 24).

7) CONCLUDING REMARKS AND FUTURE DIRECTIONS

Increasingly, the extent to which firms (and by extension regions) prosper or perish is entrenched with how well they access, absorb and assimilate various types of knowledge. This is not to say that other resources no longer matter, because they do. Just that, for a growing number of firms their survival is closely related to the types of knowledge they are capable of producing. This understanding that firms compete on the quality of knowledge they produce treats knowledge as a heterogeneous agent, implying that certain types of knowledge are more or less valuable than others.

Throughout this study we investigated the complexity of this knowledge – as proxied by patents - and whether or not more complex knowledge was generated by local or foreign firms. Using the method of reflections methodology we examined the share of patenting activities of firms to ascertain which type of firm was generating more complex technologies. Results show that, of the ten most complex technologies in the Irish knowledge space, that seven of them are in technology classes in which the share of foreign activity is greater than 55%. This peaks for Nanotechnology*,* which is both the most complex technology (KCI = 100) and has the highest share of foreign activity (75%). That been said, this does not mean that foreign firms are exclusively producing complex technologies. Measurements consistently ranks as one of the most complex technologies and its share of foreign activity is consistently below 40%. Similarly, Biotechnology and Pharmaceuticals have a low rates of foreign activity and high KCI values.

Another important contribution of this study examined how the complexity of these technologies changed over time. Indeed, the same way the complexity of regions evolve (Balland and Rigby, 2017) so too does the complexity of technologies embedded in these regions as new technological structures rise to prominence and as old ones' decline. Again, Nanotechnology and Measurements provide good illustrations of this process. Throughout much of the 1980s these technologies where among the least complex, primarily because their socio-economic potential had yet to be realised. Yet, two decades later these technologies are consistently ranked among the most complex (both within Ireland and the EU), and are also the technologies that underpin the European Union's Smart Specialisation thesis.

In terms of future research this paper presented a model of complex regional diversification. Similar to radical innovations and unrelated regional branching, complex diversification does not conform with the teachings of evolutionary economic geography. As such, it requires a separate framework of analysis and one that explicitly considers how the complexity of technologies influence the evolution of regions. As previously discussed, the intuition behind complex diversification is fairly straightforward, chiefly, given the chance regions would prefer to diversify into more complex technological domains than those they currently specialise in. For Ireland, what matters most when trying to enact complex diversification is relatedness density. Complex technologies are more likely to enter a region when those (complex) technologies are already related to the knowledge base of a region. Next, in and of themselves the effects of complexity and relatedness exert an overall negative impact. However, when these effects are interacted their presence becomes positive and significant revealing that diversifying into a complex technological structure can be facilitated if the diversification process builds on a series of capabilities already present in the region.

Lastly, we would argue that this complex dimension has important bearings on regional development and innovation policies. Complexity ushers in a new framework through which regional economic policy should not only favour related diversification (specialization) per se, but should also target complex (unrelated) diversification as this would enable regions to jump further and into technological structures more complex than those already produced. Economic geographers have long recognised the value and importance of radical technologies and their ability to change current technological paradigms. Here we wish to extend these discussions to include a complex dimension.

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BIBLIOGRAPHY

Albeaik, S., Kaltenberg, M., Alsaleh, M., and Hidalgo, C. A. (2017) 'Improving the Economic Complexity Index', Arixv Working Paper, arXiv:1707:1–21.

Almeida, P. and Kogut, B. (1997) 'The exploration of technological diversity and geographic localization in innovation: Start-up firms in the semiconductor industry', *Small Business Economics*, 9 (1), pp. 21 - 31.

Antonelli, C., Crespi, F., Mongeau Ospina, C.A. and Scellato, G. (2016) 'Knowledge composition, Jacobs externalities and innovation performance in European regions', *Regional Studies*, pp.1-13.

Balassa, B. (1965) 'Trade liberalisation and "revealed" comparative advantage'. *The Manchester School*, 33 (2), pp.99-123.

Balland, P.A. (2016a) 'Relatedness and the Geography of Innovation', In: R. Shearmur, C. Carrincazeaux and D. Doloreux (*eds*.), *Handbook on the Geographies of Innovation*. Northampton, MA: Edward Elgar, pp. 127 – 141.

Balland, P. A. (2016) EconGeo: Computing Key Indicators of the Spatial Distribution of Economic Activities, R package. https://github.com/PABalland/EconGeo.

Balland, P.A. and Rigby, D. (2017) 'The Geography of Complex Knowledge', *Economic Geography,* 93 (1), *pp.* 1-23.

Balland, P.A. Boschma, R. Crespo, J. and Rigby, D. (2017) 'Smart Specialization policy in the EU: Relatedness, Knowledge Complexity and Regional Diversification'. Working paper No. 17.17. Available at: http://econ.geo.uu.nl/peeg/peeg.html.

Barabási, A. (2011) 'The network takeover', *Nature Physics*, 8 (1), p.14 – 16.

Bathelt, H. (2005) 'Cluster relations in the media industry: Exploring the' distanced neighbour' paradox in Leipzig', *Regional Studies,* 39 (1), pp.105-127.

Bathelt, H. and Glückler, J. (2014) 'Institutional change in economic geography', *Progress in Human Geography*, 38 (3), pp.340-363.

Bathelt, H., Malmberg, A. and Maskell P. (2004). 'Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation', *Progress in Human Geography*, 28 (1), pp. 31-56.

Bonaccorsi, A. and Thoma, G. (2007) 'Institutional complementarity and inventive performance in nano science and technology', *Research Policy*, 36 (6), pp.813-831.

Boschma, R. (2005) ‘Proximity and Innovation: A Critical Assessment’, *Regional Studies,* 39, (1), pp. 61 – 74.

Boschma, R. (2017) ‘Relatedness as driver of regional diversification: a research agenda’, *Regional Studies*, 51 (3), pp. 351-364.

Boschma, R., Balland, P. and Kogler, D. (2015) ‘Relatedness and technological change in cities: The rise and fall of technological knowledge in U.S. metropolitan areas from 1981 to 2010’. *Industrial and Corporate Change,* 24 (1), pp. 223-250.

Boschma, R. and Capone, G. (2015) ‘Institutions and Diversification: Related versus unrelated diversification in a varieties of capitalism framework, *Research Policy,* 44, pp. 1902-1914.

Boschma, R. and Frenken, K. (2011) ‘Technological relatedness and regional branching’, In: Bathelt, H. Feldman, M. and Kogler, D. (eds.), B*eyond Territory. Dynamic Geographies of Knowledge Creation, Diffusion and Innovation*, Routledge, London and New York, pp. 64-81.

Boschma, R. and Martin, R. (2010) ‘The aims and scope of evolutionary economic geography). In: Boschma, R. and Martin, R. (eds.), *The Handbook of Evolutionary Economic Geography*. Cheltenham, Edward Elgar, pp. 3–40.

Borgatti, S. (2009) ‘2-Mode concepts in social network analysis’. In: Meyers, R. (eds.), *Encyclopedia of complexity and system science*, London: Springer, pp. 8279–91.

Breschi, S. and Lissoni, F. (2009) ‘Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows, *Journal of Economic Geography,* 9 (4), pp. 439 – 468.

Breschi, S. and Lenzi, C. (2015) ‘The Role of External Linkages and Gatekeepers for the Renewal and Expansion of US Cities’ Knowledge Base, 1990-2004’ *Regional Studies,* 49 (5), pp. 782-797.

Caldarelli, G., Cristelli, M., Gabrielli, A., Pietronero, L., Scala, A. and Tacchella, A. (2012) ‘A network analysis of countries’ export flows: firm grounds for the building blocks of the economy’, *PloS one*, 7 (10), pp. 1 – 11.

Castaldi, C., Frenken, K. and Los, B. (2015) ‘Related Variety, Unrelated Variety and Technological Breakthroughs: An Analysis of U.S. State-Level Patenting’, *Regional Studies,* 49 (5), pp.767-781.

Christopherson, S., Michie, J. and Tyler, P. (2010) ‘Regional resilience: theoretical and empirical perspectives’, *Cambridge Journal of Regions, Economy and Society,* 3, pp. 3 – 10.

Colombelli, A., J. Krafft and F. Quatraro (2014) ‘The emergence of new technology-based sectors In European regions: a proximity-based analysis of nanotechnology’, *Research Policy*, 43, pp. 1681-1696.

Dosi, G. and Nelson, W. (2010) 'Technical Change and Industrial Dynamics as Evolutionary Processes', In: Bronwyn, H. and Rosenberg, N. (eds.), *Handbook of the Economics of Innovation,* Elsevier, pp. 51 – 127.

Essletzibchler, J. (2015) 'Relatedness, Industrial Branching and Technological Cohesion in U.S. Metropolitan Regions', *Regional Studies,* 49 (5), pp.752-766.

Feldman, M. and Kogler, D. (2010) 'Stylized Facts in the Geography of Innovation', In: Bronwyn, H. and Rosenberg, N. (eds.), *Handbook of the Economics of Innovation,* Elsevier, pp. 381 – 410.

Feldman, M., Kogler, D. and Rigby, D. (2015), 'rKnowledge: The Spatial Diffusion and Adoption of rDNA Methods', *Regional Studies,* 49 (5), pp. 798-817.

Fleming, L. (2001) 'Recombinant uncertainty in technological search', *Management science*, 47 (1), pp.117-132.

Fleming, L. and Sorenson, O. (2001) 'Technology as a complex adaptive system: evidence from patent data', *Research policy*, 30 (7), pp.1019-1039.

Foray, D., David, P. and Bronwyn, H. (2011) 'Smart specialization. From academic idea to political instrument, the surprising career of a concept and the difficulties involved in its implementation' *Working Paper No. 170252* Available at: https://infoscience.epfl.ch/record/170252/.

Frenken, K., Van Oort, F. and Verburg, T. (2007) 'Related Variety, Unrelated Variety and Regional Economic Growth', *Regional Studies,* 41 (5), pp. 685-697.

Gertler, M. (2003) 'Tacit Knowledge and the Economic Geography of Context or the Undefinable Tacitness of Being (There)', *Journal of Economic Geography,* 3 (1), pp.75-99.

Giuliani, E. (2011) 'Role of technological gatekeepers in the growth of industrial clusters: Evidence from Chile', *Regional Studies*, 45 910) pp.1329-1348.

Glucker, J. (2007) 'Economic geography and the evolution of networks', *Journal of Economic Geography*, 7 (5), pp. 619-634.

Grabher, G. (2009) 'Yet another turn? The evolutionary project in economic geography', *Economic Geography,* 85 (2), pp.119-127.

Griliches, Z. (1990) 'Patent statistics as economic indicators: A survey', *Journal of Economic Literature,* 28, pp. 1661–707.

Hausmann, R. and Klinger, B. (2007) 'The structure of the product space and the evolution of comparative advantage', Working paper no. 146. Cambridge, Mass.: Centre for International Development, Harvard University.

Hausmann, R., Hidalgo, C., Bustos, S., Coscia., Chung, S., Jimenez. J., Simoes. A. and Yıldırım. M. (2011) *The Atlas of Economic Complexity. Mapping Paths to Prosperity.* MIT Press.

Hausmann, R. and Neffke, F. (2016) 'The workforce of pioneer plants', *HKS Working Paper No. 16-006* Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2782643.

Hidalgo, C. (2015) *Why Information Grows. The Evolution of Order, from Atoms to Economics.* New York: Basic Books.

Hidalgo, C., and Hausmann, R. (2009) 'The building blocks of economic complexity', *Proceedings of the National Academy of Sciences* 106:10570–5.

Hidalgo, C., Klinger, B., Barabassi, A. and Hausmann, R. (2007) 'The product space conditions the development of nations', *Science*, 317 (5837), pp. 482–487.

Hodgson, G. (2004) *The evolution of institutional economics*. London, Routledge.

Hoekman, J., Frenken, K. and Tijssen, R. (2010) 'Research collaboration at a distance: Changing spatial patterns of scientific collaboration within Europe', *Research Policy*, 39 (5), pp. 662-673.

Howells, J.R. (2002) 'Tacit knowledge, innovation and economic geography', *Urban studies*, 39 (5-6), pp.871-884.

Inkpen, A. and Tsang, E. (2005) 'Social capital, networks, and knowledge transfer', *Academy of management review*, 30 (1), pp.146 - 165.

Jacobs, J. (1969) *The Economy of Cities.* Random House: New York.

Jaffe, A., Trajtenberg, M. and Henderson, R. (1993) 'Geographic localization of knowledge spillovers as evidenced by patent citations', *Quarterly Journal of Economics*, 63, pp. 577-598.

Kauffman, S. (1993) *The Origins of Order*. Oxford University Press, New York.

Kogler, D. (2015) 'Editorial: Evolutionary Economic Geography – Theoretical and Empirical Progress', *Regional Studies,* 95 (5), pp. 705-711.

Kogler, D., Rigby D. and Tucker, I. (2013) 'Mapping Knowledge Space and Technological Relatedness in US Cities'. *European Planning Studies*, 21 (9), pp. 1374-1391.

Kogler, D., Essletzbichler, J. and Rigby, D. (2016) 'The evolution of specialization in the EU15 knowledge space', *Journal of Economic Geography,* 17 (2), pp. 345 – 373.

Krugman, P. (1991) 'Increasing returns and economic geography', *Journal of political economy*, 99 (3), pp.483-499.

Leydesdorff, L. and Schank, T. (2008) 'Dynamic animations of journal maps: Indicators of structural changes and interdisciplinary developments', *Journal of the American Society for Information Science and Technology*, 59 (11), pp.1810-1818.

Lundvall, BA (1992) *National Systems of Innovation* London: Printer.

Mas Tur, E. (2016) *Understanding the social dimension of knowledge through complex network analysis.* PhD thesis, Utrecht University, Utrecht, the Netherlands.

Malmberg, A. and Maskell, P. (2006) 'Localized learning revisited', *Growth and Change*, 37(1), pp.1-18.

Maskell, P. and Malmberg, A. (1999) 'The competitiveness of firms and regions: "ubiquitification" and the importance of localized learning', *European Urban and Regional Planning Studies*, 6 (1), pp. 9- 25.

Markusen, A. (1996) 'Sticky places in slippery space: a typology of industrial districts', *Economic geography*, 72 (3), pp.293-313.

Martin, R. and Sunley, P. (2006) 'Path dependence and regional economic evolution', J*ournal of Economic Geography*, 6 (4), pp.395-437.

McCann, P., & Ortega-Argilés, R. (2013) 'Transforming European regional policy: a results-driven agenda and smart specialization', *Oxford Review of Economic Policy*, 29 (2), pp. 405-431.

McCann, P., & Ortega-Argilés, R. (2015) 'Smart specialization, regional growth and applications to European Union cohesion policy', *Regional Studies* 49 (8), pp. 1291-1302.

Metcalfe, J. (1994) 'Evolutionary economics and technology policy', *The economic journal*, 10(425), pp.931-944.

Morrison, A. and Rabellotti, R. (2009) 'Knowledge and information networks in an Italian wine cluster' *European Planning Studies*, 17 (7), pp.983-1006.

O'Clery, N. (2015) 'A Tale of Two Clusters: The Evolution of Ireland's Economic Complexity since 1995', *Journal of the Statistical and Social Inquiry Society of Ireland,* XLV, pp. 16 – 66.

Nicolis. G. and Prigogine, I. (1989) *Exploring Complexity: An Introduction.* St. Martin's Press.

Nelson, R. and Winter, S. (1982) *An Evolutionary Theory of Economic Change*. Cambridge: The Belknap Press.

Neffke, F., Henning, M. and R. Boschma (2011), 'How do regions diversify over time? Industry relatedness and the development of new growth paths in regions,' *Economic Geography*, 87, pp. 237–265.

Neffke, F., Otto, A. and Hidalgo, C. (2016) 'The mobility of displaced workers: How the local industry mix affects job search strategies' (No. 1605). *Utrecht University, Section of Economic Geography.* Available at: http://www.frankneffke.com/files/NeffkeOttoHidalgo_DisplacedWorkers.pdf.

Pavitt, K. (1984) 'Sectoral patterns of technical change: towards a taxonomy and a theory', *Research policy*, 13 (6), pp 343 – 373.

Penrose, E. (1959), *The Theory of the Growth of the Firm.* Oxford: Oxford University Press.

Polanyi M., 1967. *The Tacit Dimension*, Doubleday: New York.

Quatraro, F. (2010) ‘Knowledge coherence, variety and productivity growth: Manufacturing evidence from Italian regions’, *Research Policy,* 39 (10), pp.1289–1302.

Rigby, D. (2000) ‘Geography and Technological Change’. In: Sheppard, E. and Barnes, T. (eds.), A Companion to Economic Geography. Blackwell Publishing, Oxford, pp. 202 – 222.

Rigby, D. (2015) ‘Technological relatedness and knowledge space. Entry and exit of US cities from patent classes’, *Regional Studies,* 49 (11), pp. 1922-1937.

Saxenian, A. (1994) *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*, Cambridge: Harvard University Press.

Schmoch, U. (2008) *Concept of a technology classification for country comparisons. Final report to the world intellectual property organization (wipo),* WIPO.

Schoenmakers, W. and Duysters, G. (2010) ‘The technological origins of radical inventions’, *Research Policy*, 39 (8), pp.1051-1059.

Schumpeter, J. (1939) *Business Cycles*. New York: McGraw-Hill.

Schumpeter, J. (1942) *Capitalism, Socialism and Democracy*. New York: Harper.

Simon, H. (1962) ‘The architecture of complexity’, Proce*edings of the American philosophical society*, 106 (6), pp.467-482.

Sonn, J.W. and Storper, M. (2008) ‘The increasing importance of geographical proximity in knowledge production: an analysis of US patent citations, 1975–1997’, *Environment and Planning A,* 40 (5), pp.1020-1039.

Storper, M. (1995) ‘The resurgence of regional economies, ten years later: the region as a nexus of untraded interdependencies’, *European urban and regional studies*, 2 (3), pp.191-221.

Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A. and Pietronero, L. (2012) ‘A new metrics for countries’ fitness and products’ complexity’, *Nature Scientific Reports*, 2, pp. 1 – 7.

Tanner, A. (2014) ‘Regional branching reconsidered: Emergence of the fuel cell industry in European regions’, *Economic Geography*, 90 (4), pp. 403-427.

Tanner, A. (2016) ‘The emergence of new technology-based industries: the case of fuel cells and its technological relatedness to regional knowledge bases’, *Journal of Economic Geography*, 16 (3), pp. 611-635.

Thompson, P. and Fox-Kean, M. (2005) ‘Patent citations and the geography of knowledge spillovers: A reassessment’, *American Economic Review*, 95 (1), pp.450-460.

Usai, S. (2011) 'The geography of inventive activity in OECD regions', *Regional Studies* 45 (6), pp. 711-731.

Whittle, A. and Kogler, D. (2017) 'Related to What? Reviewing the Literature of Technological Relatedness: Where we are now and Where can we go'. Draft manuscript available from the authors.

Zucker, L., Darby, M. and Armstrong, J. (1998) 'Geographically localized knowledge: spillovers or markets?', *Economic Inquiry*, 36 (1), pp.65-86.

Zhu, S., He. C. and Zhou, Y. (2015) 'How to jump further? Path dependent and path breaking in an uneven industry space'. Working paper No. 15.24. Available at: http://econ.geo.uu.nl/peeg/peeg.html.